Data & Knowledge Engineering 116 (2018) 80–99

Contents lists available at ScienceDirect

Data & Knowledge Engineering

journal homepage: www.elsevier.com/locate/datak

A multiple criteria credit rating approach utilizing social media data

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ARTICLE INFO

Keywords:
Credit rating
Cumulative belief degrees
Sentiment analysis
Social media
Web mining
Text mining

ABSTRACT

Credit rating is a process for building a classification system for credit lenders to characterize current or potential credit borrowers. By such a process, financial institutions classify borrowers for lending decision by evaluating their financial and/or nonfinancial performances. Recently, use of social media data has emerged an important source of information. Accordingly, social media data can be very useful in evaluating companies' credibility when financial or non-financial assessments are missing or unreliable as well as when credit analyzers' subjective perceptions manipulate the decision. In this study, a multiple criteria credit rating approach is proposed to determine companies' credibility level utilizing social media data as well as financial measures. Additionally, to strengthen the lender's interpretation and inference competency, ratings are represented with a risk distribution based on cumulative belief degrees. Sentiment analysis, a web mining and text classification method, is used to collect social media data on Twitter. Importance of criteria is revealed through pairwise comparisons. Companies' performance scores and ratings are obtained by a cumulative belief degree approach. The proposed approach is applied to 64 companies. Results indicate that social media provides valuable information to determine companies' creditability. However credit ratings tend to decrease when social media data is considered.

1. Introduction

In the banking sector, "credit" can be defined as allowing certain individuals or organizations to access specific resources with an agreement imposing predetermined conditions for both the lender and borrower [28]. The bank should measure this risk's magnitude and potential influence in order to build an effective credit risk management system.

The fundamental task of credibility measurement is the classification of applicants into risk groups. An applicant demonstrating good characteristics with regard to repayment strength and intention is considered as a creditworthy applicant. If an applicant has bad indications, it may be seen as an uncreditworthy one. The creditworthy applicants can be sorted into many groups with different purposes, such as determining credit limits and conditions stipulated by the lender.

Many classical and contemporary methods were developed in the credit rating literature. In the earlier years, statistical methods (such as discriminant analysis, linear or logistic regression, probit analysis) were mostly exploited, but contemporary (intelligent) approaches such as machine learning, genetic programming, rough set theory, and fuzzy logic have become popular during the last two decades.

Particularly, the credit rating industry has been in turmoil since the great recession of 2007–2008 as even the top rating agencies

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https://doi.org/10.1016/j.datak.2018.05.005
Received 3 August 2017; Received in revised form 23 January 2018; Accepted 21 May 2018
Available online 29 May 2018
0169-023X/

were exposed to severe criticisms because of their misevaluations [29]. Thus, researches from many academic areas have aimed to build more powerful credit rating models, such as artificial intelligence techniques like [15,39,40] or genetic algorithms like [14,16]. Many different techniques like multiple criteria decision making ([18,45]), data envelopment analysis ([9,37]) and fuzzy logic ([2,41,42]) are still being investigated in academic researches.

Credit rating is based on the assessment of a company in terms of its financial and non-financial criteria [12]. Financial measures are the monetary facts that are represented by ratios such as quick ratio, debt ratio, inventory turnover and profit margin before tax. Non-financial criteria, on the other hand, are considered regarding the commercial, managerial, and organizational activities of applicant organizations. Examples of these measures are the adaptability of organizations to strategic plans, improvement of customer satisfaction, and the future projection of a novel product/service, etc. However, since they include subjective evaluations, processing and quantification of non-financial measures are much more difficult than financial measures.

Nowadays, a simple page of news broadcasted in an online environment, a situation assessment or a mention circulating on social media (for instance, microblogs like Twitter, Instagram, Facebook, or news pages on the Internet) have the potential to change the whole agenda throughout a given country. Accordingly, data gathered from the social network accounts of companies may be considered an important source of information. For example, Zhang et al. [44] built a credit rating method considering social media information for online peer-to-peer (P2P) lending issue. The relation between the social media efficiency of a company and its financial situation (i.e., share prices) was studied by Kang and Park [24], Schniederjans et al. [34] and Wei et al. [38].

The modern financial sector is now faced with a situation in which the reliability of perceptions made by credit analyzers based on financial or non-financial measures has become insufficient for the complete assessment of credit rating [13]. Furthermore, some organizations may actually apply for credit with insufficient, improper, manipulated or deceptive information [1]. Qualitative assessments based on expert judgments of a credit committee in a bank gain particular importance for this kind of manipulative application. In this case, credit analyzers utilize data on social media and other internet resources in order to strengthen their perception about the applicant's reliability and repayment capability.

Using social media data, e.g. Facebook, Twitter, LinkedIn for credit rating was widely described in popular media. By their article published in “TheNation.com”, Taylor and Sadowski [36] stated that Facebook data of individuals who do not have any credit history are utilized by small on-line credit granting companies and the institutional social media accounts of start-ups are usable for the same purpose. Similarly, Credeur [10] published an article in “Bloomberg.com” expressing that Kabbage, a small on-line credit granting start-up from Atlanta (USA), utilizes social media data like the user feedbacks in Amazon.com and Yahoo! while evaluating the credibility of the applicant companies which are mostly on-line sellers. There are also other companies that professionally use social media data for credit rating. For example, Lenddo has already use information of users from Facebook, LinkedIn and Twitter to evaluate credit risks of the customers. There are some basic drawbacks about these applications. These systems' methodological details are not explicitly explained nor are the algorithms presented. So, one cannot scientifically verify or validate them or analyze its competencies.

To our best knowledge, there is no methodology in the literature that systematically integrates social media data and the classical criteria for credit rating. The basic aim of this study is to propose a multiple criteria credit rating approach that considers social media while determining the credit rating of companies. Besides, the ratings are represented with a risk distribution based on belief degrees to strengthen the lender's interpretation and inference competency. The proposed approach consists of three steps. Initially, Sentiment Analysis (SA) is utilized in order to generate the social media data of organizations. Subsequently, various kinds of criteria, such as financial and non-financial ones, in the credit rating problem are prioritized using the pairwise comparisons. Finally, Cumulative Belief Degree (CBD) approach is used for obtaining the performance scores and aggregating them into a credit rating. The outcome of this analysis is the risk distribution of the company among specific credit ratings. In this respect the main contributions of this study can be listed as follows:

(1) A novel approach for credit rating based on CBDs.
(2) Use of social media data in credit rating process.
(3) Representation of the credit ratings of companies via distributions (i.e. cumulative belief structure).

The rest of the paper is organized as follows. The background of the credit rating problem and literature review is summarized in section 2. The methods used in the proposed approach are introduced in Section 3. The proposed approach is explained in detail in Section 4. In order to demonstrate the applicability of the methodology, the results of a real life case study are presented in Section 5. Section 6 discusses the outcomes of the experimental study, and Section 7 completes the study with the results and future research agenda.

2. Credit rating

2.1. Fundamentals of credit rating

Altman and Saunders [5] emphasizes the five developments of the last two decades of the twentieth century that forced the banks to measure their credit risk by using more effective credit rating tools: increase in the number of bankruptcies, a trend towards disintermediation, more competitive margins on credits, decline value of real assets and growth of off-balance sheet instruments with inherent default risk exposure, include credit risk derivatives. The accuracy of rating assignments is vital for the banks to sustain itself and to remain financially effective [12]. For these reasons, an improved credit rating method should really have been developed with

Table 1
The most popular credit ratings.

	Standard & Poor's		Moody's	
	Long and Medium Term	Short Term	Long Term	Short Term
Investment Grade	AAA, AA, A, BBB	A-1, A-2, A-3, B-1	Aaa, Aa, A, Baa	Prime-1, 2
Speculative Grade	BB, B, CCC, CC, C	B-2, B-3, C	Ba, B, Caa, Ca, C	Prime-3
Rejection Grade	D	D	–	–

higher classification capability.

The basic aim of a credit rating method is to distribute the credit applicants into many risk classes representing the overall repayment capacity. For this, quantitative assessment methodologies have been built possessing accurate prediction capability. In a credit rating method, there are three different risk groups. The first is the investment grade which includes the more reliable customers with regard to repayment strength. The second is called the speculative grade in which companies should be evaluated more carefully. The stipulated credit conditions of the organizations rated in the second grade are sharper than the organizations rated in the first grade ratings. Finally, the third group is called the rejection grade. These organizations have poor performance scores in terms of the credit rating criteria and their repayment capability is not sufficient to assign a credit limit [11]. Two popular bureaus' credit ratings are summarized in Table 1.

In the literature, there are many examples of credit rating methods. Crouhy et al. [11] proposed a prototype rating methodology involving nine consecutive steps. This approach has many similar aspects with the current systems applied in the banking sector. The steps are financial evaluation, managerial evaluation, industrial evaluation, quality evaluation of financial data, evaluation of country risk, scrutinizing of the third party support, term evaluation, structural evaluations regarding provided indemnity and evaluation of collateral. Each lender may differentiate its credit rating method in accordance with its distinctive processes, rating approach, expectations, requirements and available data.

2.2. Criteria for credit rating

Credit rating is essentially a classification problem because the credit applicants are required to be assigned into different risk classes called credit ratings. Ishizaka and Nemery [17] state that there are three kinds of classification: nominal classification which does not consider the importance order between classes; ordinal classification (called sorting) which considers that the predetermined classes have importance orders ($C_1 \succ C_2 \succ ... \succ C_b$); and clustering or uncontrolled classification which includes no predefined classes. In terms of this grouping, credit rating issue is involved in sorting (ordinal classification) problem type because there is a set of credit ratings that represent the ordered risk levels and have their own lower and upper numerical limits. Therefore, MCDM methods for sorting are appropriate methods for credit rating problem.

As the problem is considered as an MCDM problem, the criteria for credit rating should be identified clearly. Commercial credit rating criteria may generally be classified into three: financial, non-financial, and social media. Examples for the sub-criteria of these main criteria are given in Fig. 1.

Financial criteria measure an applicant's performance and reimbursing capability based on its financial statements [8]. In practice, credit analyzers are dealing with these financial measurements, because they can uncover the applicant's default possibility. There are many financial ratios in the literature, but the current paper uses 10 criteria (proposed by Refs. [19] and [35]), clarifying their easiness on the issue of fuzzification. There are 4 main categories:

- Liquidity:

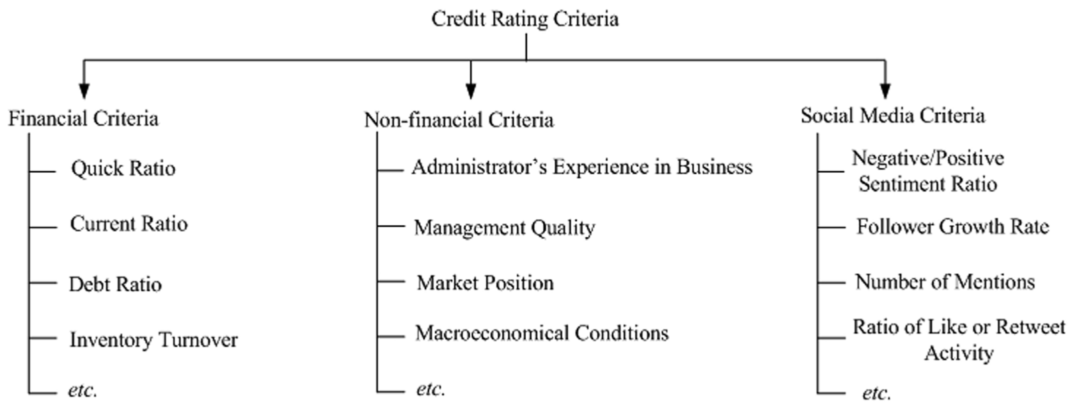

Fig. 1. Hierarchy of credit rating criteria.

  - $Current\ Ratio = Current\ Assets/Current\ Liabilities$: This specifies whether an applicant's short term assets are sufficient to refund its short-term liabilities.
  - $Quick\ Ratio = (Current\ Assets - Inventories)/Current\ Liabilities$: This strengthens the former ratio by eliminating the inventories which are more difficult to turn into cash.
- Financial Structure
  - $Debt\ Ratio = Total\ Debt/Net\ Worth$: This is concerned with the amount of leverage (money borrowed from outside of the company) being utilized by an applicant.
  - $Long-term\ Asset\ Efficiency\ Ratio = \frac{Fixed\ Assets + Long-term\ Investments}{Net\ Worth + Total\ Long-Term\ Debt}$: This analyzes how well an applicant uses its fixed assets and the degree of its efficiency with long-term investments.
- Profitability
  - $Interest\ Expenses\ to\ Net\ Sales\ Ratio = Interest\ Expenses/Net\ Sales$: This intimates the amount of net income that was spent to repay the interest of borrowed money.
  - $Profit\ Margin\ Before\ Tax = Income\ Before\ Tax/Net\ Sales$: This is a measure of the operating efficiency of an applicant and explains its capability of turning sales into profit.
  - $Return\ on\ Net\ Worth\ Before\ Tax = Income\ Before\ Tax/Net\ Worth$: This measures the earnings before taxes for each monetary unit of investment.
- Efficiency
  - $Inventory\ Turnover = Cost\ of\ Sales/Average\ Inventory$: This demonstrates how many times an applicant's inventory is replaced over a period.
  - $Receivables\ Turnover = \frac{Net\ Sales}{Average\ Notes\ and\ Accounts\ Receivable}$: This quantifies an applicant's capability on the issue of collecting debts in terms of credit.
  - $Total\ Assets\ Turnover = Net\ Sales/Total\ Assets$: This measures the efficiency of an applicant's usage of the assets in generating sales revenue.

Non-financial criteria comprise the second type. Based on the analysis executed on the credit files of 4 main German banks, Grunert et al. [13] found that non-financial criteria lead to a more accurate prediction of future defaults by strengthening the prediction power of financial criteria. It can vary in terms of the lenders' preferences, expectations or considerations. For example, Grunert et al. [13] considered management quality and market position as non-financial criteria; the manager's personal credits and his/her experience in business, stockholders' structure type and outstanding check records in banks were taken into account by Jiao et al. [19]; Yurdakul and İç [43] analyzed 3 main non-financial criteria categories: revenue generation capacity (market situation and country status), cost control capacity (plant location, production units and managerial issues) and other factors (years in business, legal status, guarantees, strategic plans, etc.)

In practice, non-financial measurements are dependent on subjective judgments [8]. In order to strengthen this assessment of the applicant's performance, effectiveness of the applicant's social media use is proposed as a support for its non-financial assessment in this study.

2.3. Social media data for credit rating

Kosinski et al. [25] claim that the personal aspects and preferences of individuals can be predicted by analyzing their digital footprints. In order to demonstrate this idea's validity, they conducted a survey involving the Facebook accounts of 58466 volunteers. The personality of the volunteers was measured by 3 different psychological tests. Statistical analysis (logistic/linear regression) confirmed the hypothesis validity. For example, the accurate prediction percentages were found to be 95% for the division of Afro-American and white American, 93% for age, 88% for sexual preference. Similarly, Wei et al. [38] state that social media can be used for credit rating. They propose a social media data based model for the evaluation of credit applications, but considered social media data in isolation and did not integrate it with the financial or non-financial data of the applicant. Zhang et al. [44] tried to build a credit rating methodology considering social media information for online peer-to-peer (P2P) lending issue. They exploited an online Chinese P2P platform for gathering social network information about applicant companies and they analyzed these social media data with a data mining approach, namely decision trees. Their work was focused on a niche credit rating problem and the social media information demonstrate on-line scoring of the platform; they do not include any customers' or other type of stakeholders' opinions or preferences.

Shared social media information can be produced and dispersed either from inside (announcements of products, services, promotions, organizational revisions or responses to customers' complaints shared by the social media related department of an organization) or outside (customer complaints and opinions about existing or new products, services, campaigns) of the organization. There are many articles studying the relations between the social media efficiency of a company and its financial situation (for example, share prices) in the literature [24,34,41]. Social media data consideration in evaluating the credibility of a company can be very useful because financial or non-financial criteria assessments can sometimes be unreliable, or the credit analyzers' perception or his/her personal expedience can manipulate the decision. Therefore, the customer oriented context of social media has a possibility about empowering the non-financial assessment of applicants.

In this study, Twitter was chosen as the source for collecting social media data because of its transparency in the collecting of shared items by each account, easiness of data processing and its popularity against social media platform competitors. Two social media criteria are utilized. The first criterion is “positive/negative sentiment ratio” which represents the perception of the applicant's customers. If this ratio is smaller than 1, it is concluded that the perception of the customers is one of dissatisfaction with the applicants' services or products. For the measurement of the number of negative and positive sharings made by social media users, sentiment analysis was exploited. The second criterion is “follower growth rate” which represents the measurement of change in the reputation, recognition and popularity level of the applicant among social media users.

3. Preliminaries

Before presenting the proposed methodology, we first introduce the methods that are used in the methodology in this section.

3.1. Sentiment analysis for collecting and analyzing social media data

The number of papers concerning the usage and quantification of social media data has increased in recent years [26]. Social media data generally consist of opinions, statements and comments shared by the followers of a company. Social media analysis basically aims to classify these sharings according to their intention: positive, negative or neutral perspectives. Sentiment analysis is one of the most preferred text mining methods making the social media data suitable to be operationalized. It is a machine learning based methodology using software trained to separate the sharings spread by social media tools in terms of their tendency.

Medhat et al. [30] describe sentiment analysis as a computational study of people's opinions, attitudes and emotions toward an entity which can represent individuals, events or topics. They define three main classification levels of sentiment analysis: document-level, sentence-level, and aspect-level sentiment analysis. Document-level sentiment analysis aims to classify an opinion document as expressing a positive or negative opinion or sentiment. It considers the whole document as a basic information unit. Sentence-level sentiment analysis aims to classify the sentiment expressed in each sentence. Aspect-level sentiment analysis aims to classify the sentiment with respect to the specific aspects of entities. The first step is to identify the entities and their aspects. The opinion holders can give different opinions for different aspects of the same entity, as with this sentence: “The voice quality of this phone is not good, but the battery life is long”.

Sentiment analysis is a computational tool studied by computer engineers and machine learning experts. There are many techniques focusing on the domain: Naïve Bayes, Maximum Entropy, Neural Network, Bayesian Network, Support Vector Machines, Rule-based Classification, Decision Trees, etc. [30]. In this study, we choose to utilize support vector machines (SVMs). The main principle of SVMs is to determine linear separators (hyperplanes) in the search space which can best separate the different classes. A hyperplane provides the best separation between the classes when the normal distance of any of the data points is the largest, so it represents the maximum margin of separation.

According to Altınel et al. [3], the common mathematical representation of linearly separable space can be given by Eq. (1) where w is the weight vector, b is a bias and d is the document vector to be classified.

$$w^T\varphi(d) + b = 0 \tag{1}$$

The problem of finding an optimal separating hyperplane may be solved by linearly constrained quadratic programming which is modelled as given in Eq. (2) where $\zeta = (\zeta_1, \zeta_2, ..., \zeta_l)^T$ is the vector of slack variables and C is the regularization parameter that is used to make a balance between training error and generalization.

$$\min \frac{1}{2}w^2 + C\sum_{i=1}^{l}\zeta_i \text{with the constraints } y_i(w^T\varphi(d) + b) \geq 1 - \zeta_i \quad (\zeta_i \geq 0, \forall\ i) \tag{2}$$

The problem in Eq. (2) can be solved by utilizing Lagrange method. The decision function can be formulated as given in Eq. (3) where α_i is a Lagrange multiplier, k is a proper kernel function and samples d_i with $\alpha_i > 0$ are termed support vectors.

$$f(x) = sgn\left(\sum_{i=1}^{l}\alpha_i y_i k(d_i, d_j) + b\right) \tag{3}$$

Kernel function can be accepted as a kind of similarity measure which gauges the similarity values of data points in documents. Even though there are many kernel functions (linear, polynomial and RBF kernels), the linear one is preferred because of its similarity measurement power as stated by Altınel et al. [4]. The kernel function is based on the inner products of the feature vectors of the documents (Eq. (4)). It captures similarity between two documents in so far as the terms they share. This yields certain problems due to the nature of natural language such as synonymy and polysemy since it does not consider semantic relations between terms.

$$k(d_i, d_j) = d_i d_j \tag{4}$$

In this study, sentiment analysis is utilized for calculating the chosen applicants' performance scores for social media criteria, e.g. positive and negative tweet ratio collected from applicants' Twitter accounts. These criteria represent the sentiments of their followers and are informative and supportive of their non-financial featured performance. Generally, social media analysis through sentiment analysis can be accepted as capturing and quantifying the perspective of customers. In application, the tweets were collected by using mongoDB database management system. All the analysis was carried by a special software, which directly uses WEKA on a computer with two Intel (R) Xeon (R) CPUs at 2.66 GHz with 64 GB of memory.

3.2. Pairwise comparison for weighting of criteria

In order to aggregate the performance scores of the applicants (i.e., financial, non-financial and social media data), it is required to prioritize the performance scores to reflect their relative importance. The weights for prioritization are mostly determined subjectively. This subjectivity originates from the idea of collecting and analyzing the credit analyzers' preferences regarding the importance levels of criteria [43].

According to Miller [31], people are generally more consistent when they do pairwise comparisons than when they just assign relative weights to the criteria. Therefore, when different approaches such as Rating, Point Allocation, Ratio, Ranking, Pairwise Comparison, and Trade-off are examined, Pairwise Comparison is found to be the most efficient as decision makers' focus on only two alternatives at each time [7,27]. Furthermore, since decision makers are not affected by external factors while finding the relative importance of two criteria, and mostly have deep knowledge with which to compare the two criteria, the results of the pairwise comparisons are generally more accurate compared to the other weighting methods [6,7]. Pairwise comparison is also the main aspect of Analytical Hierarchy Process, which is one of the most common approaches in decision making literature [33].

Thus, pairwise comparison is selected as an effective method for establishing the priorities of performance scores in the credit rating problem.

3.3. CBD approach for aggregating performance scores

In this study, the credit ratings are represented by risk distributions using CBDs. Jiao et al. [19] argue that the credibility of an applicant is determined by considering many indicators, both financial and non-financial. They are mostly linguistic, vague and frequently conflicting with each other. This vagueness originates from the dynamic nature of the credit rating problem and its time–dependent situation [35]. For example, an applicant that had lower credibility evaluation represented by a low credit rating last year can improve its financial strength and can deserve a better credit rating this year.

Another concern about vagueness of the credit rating problem is about the utilization of financial criteria evaluation tables that are designed for scorecard implementations. These financial ratio tables will be exploited in the proposed methodology. They consist of confidence intervals determined for each risk representation (i.e. linguistic term) level. These tables have unique interval distributions established for each financial indicator. Furthermore, non-financial indicators are mostly required to be evaluated with the judgment of human experts, i.e. credit analyzers. The financial ratio tables' evaluation and expert judgments on the evaluation of non-financial criteria can be dealt with by fuzzy logic [8].

Kabak and Ruan [21] and Kabak and Ruan [22] utilized CBDs approach evaluation of nuclear safeguards. Ruan et al. [32] proposed a CBDs approach and exploited 7 linguistic terms representing the ordinal risk classes for the decision problem on the determination of the best energy policy for a country. Kabak et al. [20] used 5 linguistic terms to identify the risk classes for energy policy evaluation problem in Turkey. Kabak et al. [23] proposed a CBD approach for analyzing the competitiveness of the automotive industry and identified five linguistic terms for the evaluation of competitiveness indicators.

CBDs approach exploits the linguistic terms of fuzzy logic in order to describe the risk classes. For the current problem, implied risk levels are credit ratings. In this study, linguistic terms are used for the representation of the information by belief structures. The credit rating of an applicant can be identified by belief structures that can be illustrated by linguistic term sets: $S = \{s_i\}$, i ε {0,1, …,4}. Each credit rating criterion is represented by its own linguistic term set. The banks mostly use the letters A, B, C, D and E for credit rating representation. The credit ratings of a credibility assessment system can be accepted as the linguistic terms. Accordingly, s_4 represents the best situation (A) and consolidates the most powerful applicants in terms of financial and non-financial assessments; s_0 represents the worst situation (E) and contains the weakest companies that should be rejected. The other ratings can be represented in an ordinal order, so we have the following credit ratings to linguistic terms: s_0: E, s_1: D, s_2: C, s_3: B, s_4: A.

The belief structure represents the general belief on a specific decision criterion. General belief is represented by a distribution among linguistic terms in this method. For example, an applicant's performance score belonging to a specific criterion can be evaluated by a credit analyzer and he/she can assign this applicant to rating B with a 30% degree and rating C with a 70% degree at the same time. In this situation, the belief degree can be formed as given in Eq. (5).

$$B(I) = \{(0.7,\, s_2),\, (0.3,\, s_3)\} \tag{5}$$

where $B(I)$ stands for the state of the criterion evaluated by the credit analyzer; s_2 and s_3 represent rating C and B, respectively; and 0.7 and 0.3 are the belief degrees. The belief degrees relevant to the other linguistic terms are zero, thus they are not shown in Eq. (5). Notice that if financial or any other data are available for evaluation, they can also be represented by a belief structure. The general definition of belief structure for the credit rating problem is shown in Eq. (6).

$$B_j(I_k) = \{(\beta_{jki},\, s_i),\, i = 0,\ldots,m\},\ \forall\, k,\ \forall\, j, \quad \sum_{i=0}^{m} \beta_{jki} \le 1,\ \forall\, k,\ \forall\, j \tag{6}$$

where j and k are indices for applicants, and credit rating criteria, respectively, i is for linguistic terms (credit ratings), β_{jki} stands for criteria k belief degree of applicant j at the credit rating level s_i.

The CBD at a certain linguistic term level can be defined as the aggregated belief degrees of greater or equal terms of the related linguistic term, i.e. belief degrees at the level of s_2, s_3 and s_4 should be summed up for calculating the CBD at the level of s_2. The CBD can be defined as given in Eq. (7).

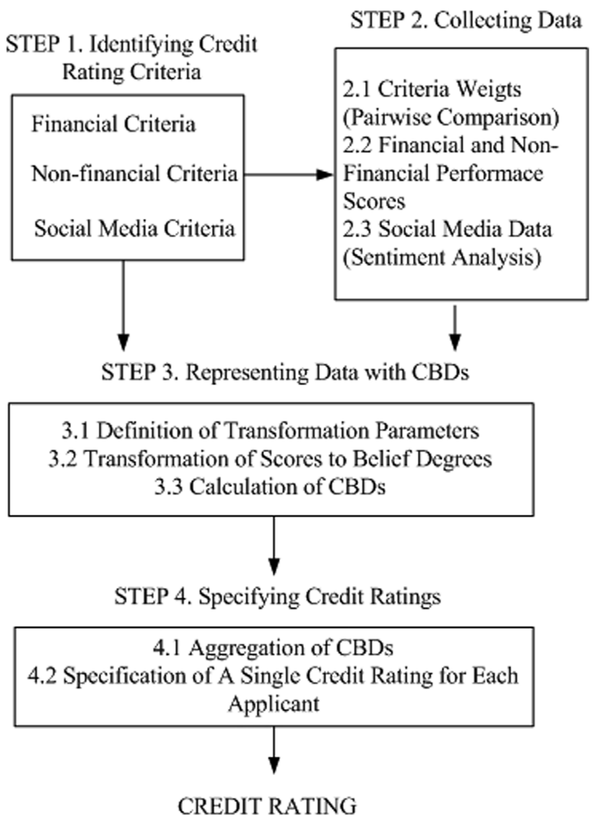

Fig. 2. Framework of the proposed methodology.

$$C_j(I_k) = \{(\gamma_{jki}, s_i),\ i = 0,\dots,m\},\ \forall\ k, \forall\ j \quad \gamma_{jki} = \sum_{p=i}^{m} \beta_{jkp} \tag{7}$$

where γ_{jki} is the CBD related to criterion k at threshold level i for applicant j. For example, $\{(0.7,\ s_2),\ (0.3,\ s_3)\}$ belief structure can be transformed to the cumulative belief structure of $\{(1,\ s_0),\ (1,\ s_1),\ (1,\ s_2),\ (0.3,\ s_3),\ (0,\ s_4)\}$.

In order to aggregate all the CBDs determined for each indicator, various methods were proposed in the literature. While Ruan et al. [32] utilized an ordered weighting averaging (OWA) operator based aggregation, Kabak et al. [20] proposed to use the subjective weights determined by decision experts. Kabak and Ruan [22] used both OWA and subjective weights together.

One of the important features of the CBDs approach is that all kinds of information represented with various types such as numerical, interval and linguistic values, or fuzzy numbers can be converted to belief degrees and further to CBDs without loss of information. Therefore; in the credit rating problem, the financial, non-financial criteria and social media data can be transformed to CBDs and aggregated to find the final ratings of the applicants. The details of the transformation formulas and aggregation procedures are given in the following subsection.

4. Proposed multiple criteria credit rating approach

This study proposes an MCDM approach for the credit rating problem. A novel methodology is designed in order to deal with different kinds of input data including financial, non-financial and social media data to find final ratings of applicant companies. The basic flow of the methodology is introduced in Fig. 2. The inputs are the data from companies that are gathered from variety of resources. The output of the methodology is the credit ratings of the companies. The methodology determines a credit rating distribution for each company with membership degrees ascertained for each rating category. We suggest an innovative representation of credit ratings that is different from existing models, where a single rating (like AAA or A+) is assigned to an applicant's credibility.

Based on Fig. 2, the steps of the proposed methodology are developed as follows:

STEP 1: Identifying Credit Rating Criteria
STEP 2: Collecting Data
2.1 Criteria weights
2.2 Financial and non-financial performance scores
2.3 Social media data

STEP 3: Representing Data with Cumulative Belief Degrees
3.1 Definition of transformation parameters
3.2 Transformation of scores to belief degrees
3.3 Calculation of cumulative belief degrees
STEP 4. Specifying Credit Ratings
4.1 Aggregation of cumulative belief degrees
4.2 Specification of a single rating for each applicant

Details of the steps of the methodology are as follows.

4.1. STEP 1: Identifying Credit Rating Criteria

As explained in Section 2.2, our approach to the credit rating problem has an MCDM perspective. In practice, different departments of the banks can be responsible for credit rating process and this responsibility may be distributed in accordance with the type, amount, and purpose of the credit applied for. The relevant credit rating problem is unique for a bank, but considered criteria and/or their weights may differ with the specifications of the customer or credit being applied for. For example, the evaluation criteria for agricultural and commercial applications vary with the specifications of their credit type. While agricultural credits are analyzed by considering the information about breeding productivity, field width, and farmer's background related with the concerned plant, evaluation of commercial applications require financial ratio analysis and non-financial investigations. Independent from the considered criteria, decisions about credit ratings are taken by utilizing the same methodology, such as logistic regression or artificial intelligence. As a result, it can be stated that all credit applications are exposed to the credit rating process. In this study, the aim is to build a credit rating approach for the sake of commercial applications.

The criteria selected for a particular context, including financial, non-financial, and social media criteria, are indexed as k, $k = 1, \ldots, K$.

4.2. STEP 2: Collecting Data

4.2.1. STEP 2.1. criteria weights

In order to aggregate performance measures determined with respect to the decision criteria above, their relative importance levels represented by weights are required. Based on the hierarchy of credit rating criteria as illustrated in Fig. 1, the pairwise comparisons are utilized for calculating the weights. To this end, initially experts evaluate the criteria in pairwise manner considering the bank's segmentation of credit applicants, their own preferences and experiences. Subsequently, if there is more than one expert, the geometric mean of the pairwise evaluations is calculated. Finally, the weight of each criterion is calculated based on the aggregated comparisons. The weights of criteria are represented by the vector $W = (w_1, w_2, \ldots, w_K)$.

4.2.2. STEP 2.2 financial and non-financial performance scores

Performance scores of financial criteria are calculated by financial ratio analysis. Financial ratio analysis basically focuses on the determination of the mathematical relation among two or more than two components of the relevant financial statement in order to make any possible interpretations about an applicant's financial strength. For instance, "current ratio" is one of the important performance criteria in credit rating process, and it is calculated by the ratio of "current assets" to "current liabilities" (i.e., $current\ ratio = \frac{Current\ Assets}{Current\ Liabilities}$). In order to determine the financial criteria performance of applicants, initially, the data related to components of the criteria are collected. Then the criteria scores are calculated based on the relevant formulae [8,19].

The non-financial performance of an applicant, on the other hand, is usually gathered by the subjective judgments of the credit analyzers or specialists. They provide the information using several scales, such as numerical values and linguistic terms. depending on their observation of the information provided by the applications, on-site inspections, etc.

All aspects of the financial or non-financial performance of an applicant constitute the main input for evaluating its credit rating. The performance of applicant j in criterion k is represented with x_{jk}.

4.2.3. STEP 2.3 social media data

Since we underline the use of social media data in the credit rating process, it is important to gather the data for the evaluation. Personal opinions, attitudes and emotions about an entity (a company, a product, a service or a person) can be directly obtained from their level of sharing on social media. The resources are blogs, forum pages, news pages or microblogs such as Twitter, or Facebook. As explained in Section 3.1, sentiment analysis, which is a computational method for gathering and processing this type of information, is utilized for this purpose. After collecting the data from a form of social media (e.g. Twitter), we generate some indices using sentiment analysis that will in turn be used to calculate criteria values. For instance, using the twitter data of an applicant we can identify positive mentions, negative mentions, increase in followers, etc. by sentiment analysis. Then scores of "Positive/Negative Sentiment Ratio" and "Follower Growth Rate" criteria are calculated as follows:

$$Positive/Negative\ SentimentRatio = \frac{Positive\ Mentions}{Negative\ Mentions} \tag{8}$$

$$Follower\ Growth\ Rate = \frac{(\#of\ Followers\ on\ the\ Last\ Day - \#of\ Followers\ on\ the\ First\ Day)}{\#of\ Followers\ on\ the\ First\ Day} \tag{9}$$

In Eq. (9), # of Followers on the Last Day, and # of Followers on the First Day relates to the last and first days of the analysis period, respectively.

This type of information is also represented by x_{jk} as in financial and non-financial performance scores.

4.3. STEP 3: Representing Data with cumulative belief degrees

To represent the criteria data with CBDs, initially a linguistic term set is defined. We used a five term linguistic term set for credit rating problem: $S = \{s_i\}, i\ \varepsilon\ \{0,1, \ldots,4\}$ where the following credit ratings are assigned to linguistic terms: s_0: E, s_1: D, s_2: C, s_3: B, s_4: A.

4.3.1. STEP 3.1. defining transformation parameters

In order to process the criteria information (i.e., x_{jk}) in the proposed approach, each performance score should be transformed to belief degrees on linguistic term sets. This transformation is based on the triangular fuzzy numbers defined particularly for each criterion. In this respect, we have to define a triangular fuzzy number with its three parameters, for each linguistic term for each criterion.

We define triangular fuzzy numbers of a criterion (criterion k) according to the most preferred (x_k^*) and least preferred (x_k^-) scores of the criterion based on standard linguistic hierarchical structures. Let triangular fuzzy number representation of linguistic term i be (a_i^L, a_i^C, a_i^R), where L and R stand for left and right supports respectively, C represents the central value. Since there are five different linguistic terms, five different fuzzy numbers should be formed.

For the benefit criteria (the greater the attribute value the more its preference), we define the triangular fuzzy numbers as follows (see Fig. 3);

$$\begin{aligned}
&\text{For } s_0;\ (a_0^L, a_0^C, a_0^R) = \left(x_k^-, x_k^-, \frac{x_k^*-x_k^-}{4}\right),\\
&\text{For } s_1;\ (a_1^L, a_1^C, a_1^R) = \left(x_k^-, \frac{x_k^*-x_k^-}{4}, \frac{x_k^*-x_k^-}{2}\right),\\
&\text{For } s_2;\ (a_2^L, a_2^C, a_2^R) = \left(\frac{x_k^*-x_k^-}{4}, \frac{x_k^*-x_k^-}{2}, \frac{3(x_k^*-x_k^-)}{4}\right),\\
&\text{For } s_3;\ (a_3^L, a_3^C, a_3^R) = \left(\frac{x_k^*-x_k^-}{2}, \frac{3(x_k^*-x_k^-)}{4}, x_k^*\right),\\
&\text{For } s_4;\ (a_4^L, a_4^C, a_4^R) = \left(\frac{3(x_k^*-x_k^-)}{4}, x_k^*, x_k^*\right).
\end{aligned} \tag{10}$$

For the cost criteria (the greater the attribute value the less its preference);

$$\begin{aligned}
&\text{For } s_0;\ (a_0^L, a_0^C, a_0^R) = \left(\frac{3(x_k^--x_k^*)}{4}, x_k^-, x_k^-\right),\\
&\text{For } s_1;\ (a_1^L, a_1^C, a_1^R) = \left(\frac{x_k^--x_k^*}{2}, \frac{3(x_k^--x_k^*)}{4}, x_k^-\right),\\
&\text{For } s_2;\ (a_2^L, a_2^C, a_2^R) = \left(\frac{x_k^--x_k^*}{4}, \frac{x_k^--x_k^*}{2}, \frac{3(x_k^--x_k^*)}{4}\right),\\
&\text{For } s_3;\ (a_3^L, a_3^C, a_3^R) = \left(x_k^*, \frac{x_k^--x_k^*}{4}, \frac{x_k^--x_k^*}{2}\right),\\
&\text{For } s_4;\ (a_4^L, a_4^C, a_4^R) = \left(x_k^*, x_k^*, \frac{x_k^--x_k^*}{4}\right).
\end{aligned} \tag{11}$$

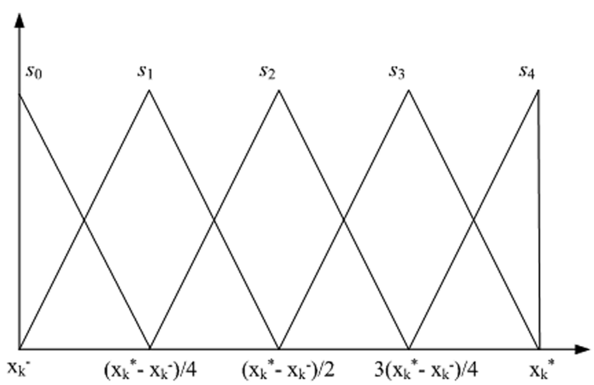

Fig. 3. Linguistic term set formation for benefit criteria.

Notice that $x_k^* \gg x_k^-$ in benefit criteria, while $x_k^* \ll x_k^-$ in cost criteria.

The triangular fuzzy numbers with their related parameters can be defined using Eq. (10) or Eq. (11) for any kind of criteria, including financial, non-financial and social media criteria, as soon as the most preferred and least preferred scores are determined. These scores can be identified through the analysis of the available information on the related criterion (for instance the maximum score can be considered the most preferred score in a benefit attribute) or according to the information provided from legal or common resources. Please see the case study for examples of determining these scores.

4.3.2. STEP 3.2 transformation of scores to belief degrees

Belief degrees represent the expectations of decision makers and include different measurement scales. Each applicant's performance values should be transformed to belief degrees in order to be handled with separated risk classes. The belief structure represents the general belief on a specific criterion and belief degrees are its elements. The transformation process is performed by using triangular fuzzy numbers' membership degree determination process [21]. For this operation, triangular fuzzy numbers defined for each criterion and for each linguistic term set are used.

The criteria for performance of applicants (x_{jk}) are transformed to belief degrees based on the membership functions associated with linguistic terms (μ_{s_k}) as follows:

For a given x_{jk};

$$\begin{aligned}&\text{If } x_k^- \le x_{jk} \le x_k^* (or\ x_k^* \le x_{jk} \le x_k^- \ for\ cost\ criteria)\\ &\qquad \beta_{jki} = \mu_{s_i}(x_{jk}), \quad \forall\ i\end{aligned} \tag{12}$$

$$\begin{aligned}&\text{If } x_{jk} < x_k^- (or\ x_{jk} > x_k^- for\ cost\ criteria)\\ &\beta_{jk0} = 1,\ \beta_{jk1} = \beta_{jk2} = \beta_{jk3} = \beta_{jk4} = 0,\end{aligned} \tag{13}$$

$$\begin{aligned}&\text{If } x_{jk} > x_k^* \ (or\ x_{jk} < x_k^* for\ cost\ criteria)\\ &\beta_{jk4} = 1,\ \beta_{jk0} = \beta_{jk1} = \beta_{jk2} = \beta_{jk3} = 0.\end{aligned} \tag{14}$$

If a criterion's performance score is between the most and the least preferred values, its belief degree is calculated according to Eq. (12). If a score in a benefit criterion is less than the least preferred value (or it is higher than the least preferred value in a cost criterion), it represents a very bad situation belonging to the worst rating. Therefore, in Eq. (13), we assign 1 belief degree to the s_0, and 0 to the others. Conversely, if a score in a benefit criterion is greater than the most preferred value, it possesses a very good situation and will definitely belong to the best rating. Therefore, in Eq. (14), we assign 1 belief degree to the s_4, and 0 to the others.

4.3.3. STEP 3.3 calculation of cumulative belief degrees

In this study, in order to represent the credit rating of an applicant as a distribution among different credit risk classes, CBD structures are used. As explained in section 3.3, the CBD at a certain linguistic term level can be defined as the aggregated belief degrees of greater or equal terms of the related linguistic term. Based on the belief degrees calculated for each criteria in the previous section, CBDs are calculated according to Eq. (7). As a result we have $C_j(I_k)$ which represents the performance of applicant k with respect to criterion j.

4.4. STEP 4. Specifying Credit Ratings

4.4.1. STEP 4.1 aggregation of cumulative belief degrees

In order to aggregate CBD structures (i.e., $C_j(I_k)$) for each applicant, the weights of criteria are considered. The aggregation operation should be executed at a certain linguistic term level. Eq. (15) shows that the aggregation process consists of the additive weighting operation for each linguistic term.

$$C_j(I) = \{(\gamma_{ji}, s_i),\ i = 0,\dots,4\}, \forall\ j \text{ where } \gamma_{ji} = \sum_k w_k \gamma_{jki} \tag{15}$$

As a result of the aggregation process, a credit rating distribution is determined for the applicant under investigation. The CBDs for each linguistic term notated by γ_{ji} represent the membership degree/general belief degree of the applicant j's credibility for credit rating s_i or higher.

4.4.2. STEP 4.2 specifying a single rating for each applicant

In order to evaluate an applicant's credit rating, a single rating as well as a CBD structure can be used. For this purpose, if necessary, credit rating distribution can be transformed to a crisp (exact, single) rating. This necessity can arise from regulations, legal obligations or personal requirements. A CBDs structure is transformed to a single linguistic term as follows:

$$R_j^\tau = \text{Sup}_{i=0,\dots,m}[s_i | \gamma_{ji} \ge \tau] \tag{16}$$

where $\tau \in [0,1]$ is a threshold value showing the risk attitude of the lender. According to Eq. (16), a single rating s_i is assigned to an applicant if s_i is the highest linguistic term having a CBD greater than or equal to τ.

Kabak et al. [20] suggest that a 50% threshold level can be used to interpreting CBDs (γ_{ji}) in such decisions like specifying the final credit rating of the applicant based on its credit rating distributions. The highest linguistic level that has a CBD greater than 50% is determined as the credit rating of the applicant. Generally, the threshold can be determined in terms of the lender's risk attitude as follows:

- If the lender has a neutral attitude, threshold value can be determined as 50% which is taken from majority principle of the group decision making.
- If the lender shows a risk avoiding attitude, the threshold value should be determined above 50%. In this circumstance, the lender prefers less risk by assigning lower credit ratings.
- If the lender is a risk seeker, the threshold value should be determined below 50%. The lender here prefers more risk, in comparison with the endured risk of the neutral attitude, by assigning higher credit ratings to applicants.

5. A case study

In order to illustrate the applicability of the proposed methodology, we conducted a real life case study. 64 companies from Borsa Istanbul (BIST), the stock exchange market of Turkey, were chosen for the experimental study. During the selection process, the social media usage density of the companies and their effectiveness in the social media environment were considered. Due to the privacy issues, we cannot mention their names or supply any kind of descriptive features.

5.1. STEP 1: Identifying Credit Rating Criteria

The proposed methodology considers all types of criteria (financial, non-financial and social media based ones), but in this case study non-financial criteria are not included due to the difficulties in reaching their scores because the privacy policies of the banks do not allow us to utilize their customer databases. The full consideration of all the criteria will be under investigation of the future researches. The non-financial criteria were ignored just for this case study. The fundamental aim is to present the applicability of the proposed methodology.

Financial criteria were selected from the most cited papers considering the fuzzy based operationalization of the credit rating process [8,19,35]. There are 10 financial criteria which were described in Section 2.2. In order to provide social media information, two social media criteria were chosen from the pool of criteria suggested by Schniederjans et al. [34]. They were based on the data collected from the micro blog site Twitter: Positive/Negative Sentiment Ratio and Follower Growth Rate. The reasons for choosing Twitter were its transparency with regard to the items shared on accounts, easiness of data processing, and its popularity against competitors. The hierarchy of the selected criteria is presented in Fig. 4.

5.2. STEP 2: data collection

5.2.1. Criteria weights

Using the hierarchy of rating criteria given in Fig. 4, we obtained the views and opinions of seven experts in order to prioritize the criteria. Five of the experts were credit analyzers who work for a bank and the other two were independent auditors. The results of

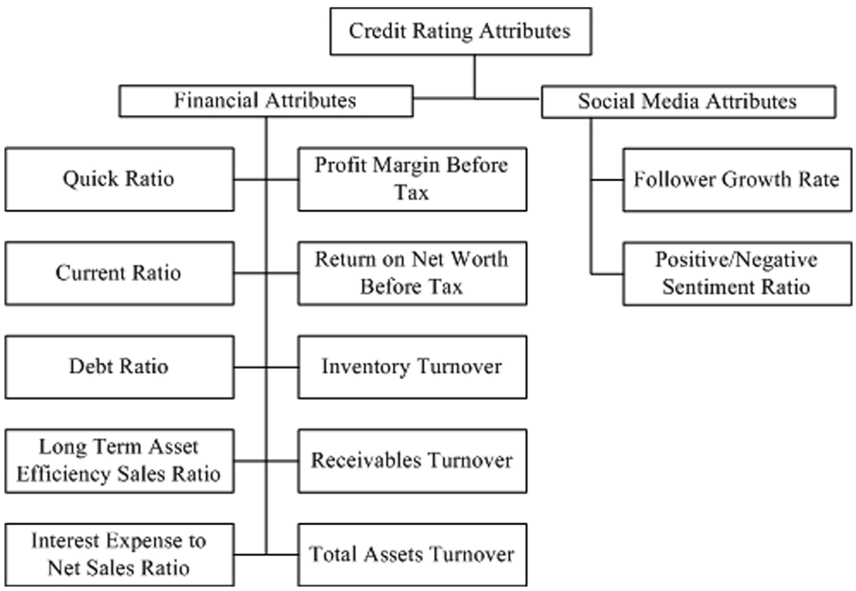

Fig. 4. Hierarchy of credit rating criteria for the case study.

Table 2
Calculation of the main criteria weights.

	Financial	Social Media	Geo. Mean	Normalized Weights
Financial	1	5.4504	2.3346	0.8450
Social Media	0.1835	1	0.4283	0.1550
		Total:	2.7629	

expert pairwise comparisons of the main criteria (i.e., financial and social media) and the criteria under the main criteria were aggregated and the final weights of the criteria (w_k, $k = 1,2, \ldots,12$) were calculated as given in Table 3.

For the illustration purposes, we give the calculation details of the weights of the main criteria. Table 2 represents the pairwise comparison matrix that includes expert group's aggregated pairwise comparisons for the main criteria. For example, 5.4504 is calculated as the geometric mean of the comparisons of seven experts: 9–7 – 3–6 – 6–7 – 3, respectively. To calculate the weights, firstly the geometric means of each row were calculated. Then, the normalization process was performed to find the main criteria weights that are depicted in the last column of Table 2. All the sub-criteria weights (the fourth column of Table 3) were calculated similarly. Final weights (the last column of Table 3) were calculated by the multiplication of the main and sub-criteria weights. For example, x_1 - Quick Ratio that is a sub-criterion of financial information gets a weight of $0.8450x0.2529 = 0.2137$.

According to the results, the financial information is found as the most important main criterion, having an importance of 84.5%. The most important financial criterion is quick ratio (25.29%), followed by receivable turnover (22.07%) and inventory turnover (10.19%). The total importance of these three criteria is 57.55% of all the financial criteria. The 42.45% remainder is distributed among the other seven criteria. This means that the first three important criteria are dominant over the other seven criteria. In terms of social media data, credit analyzers found positive/negative sentiment ratio (78.50%) more important than follower growth rate (21.50%). It may be concluded that the current customer perspective about a company is more important than the growth in the number of its followers. The final weights (the global weights with respect to goal “credit rating”) are given in the last column of Table 3.

5.2.2. *Financial performance scores*

In this step, the company's financial statements (balance sheet and statement of income) as displayed on the BIST website were examined and financial ratios were calculated for the third period of the year 2015 (April 1st – June 30th). For this purpose, the following ratios were used: current assets, fixed assets, total assets, current liabilities, total long-term debt, total debt, inventories, net worth, long-term investments, average notes and accounts receivable, interest expenses, net sales, income before tax, and cost of sales.

Based on these ratios, we calculated the criteria scores. For instance, the second criterion, current ratio, is the ratio of current assets to current liabilities. For Company 13, for example, as its reported current assets were 2,482,817 and current liabilities were 2,267,777, its current ratio can be calculated as follows:

$$x_{13,2} = \frac{Current\ Assets_{13}}{Current\ Liabilities_{13}} = \frac{2{,}482{,}817}{2{,}267{,}777} = 1.0948.$$

Similarly, calculation of Long-term Asset Efficiency Ratio, the fourth criterion, requires four kinds of ratio: fixed assets, long-term investments, net worth, and total long-term debt. The data of Company 13 in these ratios were 861,214, 535,423, 1,300,981, and 310,696, respectively, and its fourth country score was calculated as follows:

Table 3
Weights of criteria.

x_j		Weights of Main Criteria	Weights of Criteria	Final Weights of Criteria (w_k)
	Financial Information	*0.8450*		
x_1	Quick Ratio		0.2529	0.2137
x_2	Current Ratio		0.0800	0.0676
x_3	Debt Ratio		0.0296	0.0250
x_4	Long-Term Asset Efficiency Ratio		0.0552	0.0466
x_5	Interest Expense to Net Sales Ratio		0.0400	0.0338
x_6	Profit Margin Before Tax		0.0864	0.0730
x_7	Return on Net Worth Before Tax		0.0537	0.0454
x_8	Inventory Turnover		0.1019	0.0861
x_9	Receivable Turnover		0.2207	0.1865
x_{10}	Total Assets Turnover		0.0796	0.0673
	Social Media Information	*0.1550*		
x_{11}	Positive/Negative Sentiment Ratio		0.7850	0.1217
x_{12}	Follower Growth Rate		0.2150	0.0333

Table 4
Financial performance scores of selected companies.

	x_{j1}	x_{j2}	x_{j3}	x_{j4}	x_{j5}	x_{j6}	x_{j7}	x_{j8}	x_{j9}	x_{j10}
Company 1	1.4806	1.4890	2.2858	0.7953	0.0202	−0.0192	0.0000	0.7985	0.0063	0.0071
Company 9	3.0624	4.0926	0.2915	0.2460	0.0865	0.0726	0.0171	0.0050	0.0014	0.0010
Company 13	0.4991	1.0948	1.9819	0.8666	0.0128	0.0516	0.1969	0.0204	0.0270	0.0071
Company 27	1.1636	1.3686	1.2702	0.5940	0.0132	0.0097	0.0133	0.0310	0.0064	0.0033
Company 34	0.9088	1.1132	0.5051	0.9727	0.0272	0.0581	0.0727	0.1164	0.0423	0.0046
Company 47	1.6708	1.6843	0.5957	0.6905	0.0299	0.4052	0.2456	0.5841	0.0073	0.0021
Company 51	0.7097	1.1341	0.5885	0.9427	0.0051	0.0694	0.0699	0.0277	0.0192	0.0035
Company 56	1.6194	1.6318	0.5312	0.7545	0.1589	0.1722	0.0776	0.4693	0.0067	0.0016
Company 62	1.2686	1.4216	1.3257	0.7374	0.0927	0.0304	0.0177	0.0237	0.0039	0.0014
Company 63	0.4824	1.0336	3.5341	0.8996	0.0040	0.0043	0.0371	0.0258	0.0399	0.0106

$$x_{13,4} = \frac{Fixed\ Assets + Long - term\ Investments}{Net\ Worth + Total\ Long - Term\ Debt} = \frac{861214 + 535423}{1300981 + 310696} = 0.8666.$$

The performance scores of companies in the financial criteria were calculated similarly and presented in Table 4 (due to the page limitations, results of only 10 selected companies (out of 64) are provided in Table 4).

5.2.3. Social media data

Twitter was chosen for gathering social media data in the analysis due to its popularity among social media users, the appropriateness of data and the ease of data collection. First of all, we determined some identifier keywords by analyzing the official Twitter accounts of 64 companies. The goal was to allow the software performing sentiment analysis to recognize company-specific relevant Tweets that were shared by users and take these tweets into our tweet database. For instance, keywords determined for collecting tweets about a chocolate manufacturer were brand names of its products. The sentiment analysis software collected tweets including one or more of these brand names and added it into the tweet database. For the same period of time (April 1st – June 30th, 2015), we collected more than 1,500,000 tweets in this manner.

Then by using sentiment analysis, we identified the number of positive and negative mentions for each company. Moreover, we have also acquired the data of the number of followers for each company's official twitter account. Then the criteria scores were calculated as given in Eq. (8) and Eq. (9). For instance, for Company 13, the number of positive mentions was 79, the number of negative mentions was 1206, the number of followers on April 1st, 2015 was 183,038, and the number of followers on June 30th, 2015 was 215,680. Therefore, criteria scores were calculated as follows:

$$x_{13,11} = \frac{Positive\ Mentions}{Negative\ Mentions} = \frac{79}{1206} = 0.0655.$$

$$x_{13,12} = \frac{(\#of\ Followers\ on\ the\ Last\ Day - \#of\ Followers\ on\ the\ First\ Day)}{\#of\ Followers\ on\ the\ First\ Day} = \frac{(215680 - 183038)}{183038} = 0.1783.$$

With similar calculations, the social media performance scores of the companies were calculated as given in Table 5.

5.3. STEP 3: Representing Data with cumulative belief degrees

5.3.1. Defining transformation parameters

This step includes the generation of triangular fuzzy numbers for each criterion that is used to transform the performance scores to belief degrees. In this respect, triangular fuzzy numbers were defined based on the most preferred (x_k^*) and the least preferred (x_k^-) values of each criterion.

Table 5
Social media performance scores of selected companies.

	x_{j11}	x_{j12}
Company 1	0.0242	0.0870
Company 9	0.0000	−0.0062
Company 13	0.0655	0.1783
Company 27	0.1270	0.2000
Company 34	0.0441	0.2111
Company 47	0.0036	0.1915
Company 51	0.0679	0.1196
Company 56	0.0397	0.0102
Company 62	0.2857	0.0107
Company 63	0.2500	0.0678

Table 6
Triangular fuzzy numbers defined for the criteria.

	x^*	x^-	s_0	s_1	s_2	s_3	s_4
x_1	0.875	0.275	(0.275,0.275, 0.425)	(0.275,0.425, 0.575)	(0.425,0.525, 0.725)	(0.525,0.725, 0.875)	(0.725,0.875, 0.875)
x_2	1.650	0.450	(0.450,0.450, 0.750)	(0.450,0.750, 1.050)	(0.750,1.050, 1.350)	(1.050,1.350, 1.650)	(1.350,1.650, 1.650)
x_3	0.500	3.500	(3.500,4.500, 4.500)	(2.500,3.500, 4.500)	(1.500,2.500, 3.500)	(0.500,1.500, 2.500)	(0.500,0.500, 1.500)
x_4	0.633	1.633	(1.633,1.967, 1.967)	(1.300,1.633, 1.967)	(0.967,1.300, 1.633)	(0.633,0.967, 1.300)	(0.633,0.633, 0.967)
x_5	0.013	0.052	(0.053,0.067, 0.067)	(0.040,0.053, 0.067)	(0.027,0.040, 0.053)	(0.013,0.027, 0.040)	(0.013,0.013, 0.027)
x_6	0.093	−0.013	(-0.013,-0.013, 0.013)	(-0.013,0.013, 0.040)	(0.013,0.040, 0.067)	(0.040,0.067, 0.093)	(0.067,0.093, 0.093)
x_7	0.175	−0.025	(-0.025,-0.025, 0.025)	(-0.025,0.025, 0.075)	(0.025,0.075, 0.125)	(0.075,0.125, 0.175)	(0.125,0.175, 0.175)
x_8	0.067	0.013	(0.013,0.013, 0.027)	(0.013,0.027, 0.040)	(0.027,0.040, 0.053)	(0.040,0.053, 0.067)	(0.053,0.067, 0.067)
x_9	0.067	0.013	(0.013,0.013, 0.027)	(0.013,0.027, 0.040)	(0.027,0.040, 0.053)	(0.040,0.053, 0.067)	(0.053,0.067, 0.067)
x_{10}	0.013	0.005	(0.005,0.005, 0.007)	(0.005,0.007, 0.009)	(0.007,0.009, 0.011)	(0.009,0.011, 0.013)	(0.011,0.013, 0.013)
x_{11}	0.500	0.000	(0.000,0.000, 0.125)	(0.000,0.125, 0.250)	(0.125,0.250, 0.375)	(0.250,0.375, 0.500)	(0.375,0.500, 0.500)
x_{12}	0.350	0.000	(0.000,0.000, 0.0875)	(0.000,0.0875, 0.175)	(0.0875,0.175, 0.2625)	(0.175,0.2625, 0.350)	(0.2625,0.350, 0.350)

For the financial criteria, we determined the most preferred and the least preferred values based on [19]. In their study, triangular fuzzy numbers are defined for each class of financial criteria. We set the left support of the first class of a financial criterion as the most preferred value, and the right support of the last class as the least preferred value for each criterion. Because the left support of the first class represents the most undesirable (worst) situation and the right support of the last class represents the most desirable (best) situation.

After setting the most preferred and the least preferred values, the triangular fuzzy numbers were defined according to Eq. (10) (benefit criteria) or Eq. (11) (cost criteria). For instance, for the first criterion, which is a benefit criterion, $x_1^* = 0.875$, and $x_1^- = 0.275$. Therefore, the related triangular fuzzy numbers are defined according to Eq. (10) as follows:

$$\text{For } s_0;\ (a_0^L, a_0^C, a_0^R) = \left(x_1^-, x_1^-, \tfrac{x_1^* - x_1^-}{4}\right) = (0.275,\ 0.275,\ 0.425),$$

$$\text{For } s_1;\ (a_1^L, a_1^C, a_1^R) = \left(x_1^-, \tfrac{x_1^* - x_1^-}{4}, \tfrac{x_1^* - x_1^-}{2}\right) = (0.275,\ 0.425.0.575),$$

$$\text{For } s_2;\ (a_2^L, a_2^C, a_2^R) = \left(\tfrac{x_1^* - x_1^-}{4}, \tfrac{x_1^* - x_1^-}{2}, \tfrac{3(x_1^* - x_1^-)}{4}\right) = (0.425,\ 0.525,\ 0.725),$$

$$\text{For } s_3;\ (a_3^L, a_3^C, a_3^R) = \left(\tfrac{x_1^* - x_1^-}{2}, \tfrac{3(x_1^* - x_1^-)}{4}, x_1^*\right) = (0.525,\ 0.725,\ 0.875),$$

$$\text{For } s_4;\ (a_4^L, a_4^C, a_4^R) = \left(\tfrac{3(x_1^* - x_1^-)}{4}, x_1^*, x_1^*\right) = (0.725,\ 0.875,\ 0.875).$$

With similar calculations, the triangular fuzzy numbers for the criteria were defined as given in Table 6. Notice that among the twelve criteria, x_3, x_4, and x_6 are cost criteria while the rest are benefit criteria.

For the social media criteria, the literature has no suggestion for fuzzification of the social media based data or in relation to the most preferred and least preferred values. Since each social media criterion has a distinctive character, we examined them individually. Schniederjans et al. [34] statistically proved that most of the sharings on Twitter have negative perspective and followers of an account generally share their complaints and dissatisfaction about it. In this manner, Positive/Negative Sentiment Ratio (x_{11}) can be expected to be less than 1, i.e. the number of negative sentiments is expected to be higher than the number of positive sentiments. Similar to the majority rule ratio (0.5), the number of negative sentiments may double the number of positive sentiments in the most desired situation, therefore we set $x_{11}^* = 0.5$. On the other hand, the worst situation for this criterion would be having no positive mentions for a company. Therefore set $x_{11}^- = 0$ indicates no positive mentions.

For the follower growth rate (x_{12}), there is also no suggestion in the literature for the most desired or possible growth rate of follower numbers within the Twitter environment. Therefore, we analyzed the available data of the 64 companies, to set the most preferred and least preferred scores. The maximum score of the companies after eliminating the two outliers is considered to be the most preferred score ($x_{12}^* = 0.35$). The situation in which the number of followers does not change for a company can be construed as the worst case. Thus we set $x_{12}^- = 0$. After determining the most preferred and least preferred scores in the social media criteria, the related triangular fuzzy numbers were generated based on Eq. (10), as they are both benefit criteria.

5.3.2. Transformation of scores to belief degrees

Transformation of performance scores to belief degrees is realized by utilizing the triangular fuzzy numbers defined in the previous step. To illustrate the transformation process, the belief degrees calculated for Company 13 are given in Table 7. For instance, the company's quick ratio (x_1) score was 0.4991, therefore according to Eqs. (12)–(14) the related belief degrees were calculated as follows. Fig. 5 shows the calculation of membership degrees. In Fig. 5, θ and δ represents the membership degrees of a given score in the sets defined for s_1 and s_2. In the CBD approach, we use these membership degrees as belief degrees. In the example given in Fig. 5, $\theta = 0.5058$ is the belief degree related to s_1 credit rating and $\delta = 0.4942$ as the belief degree related to s_2 credit rating. According to Fig. 5, belief degrees of score 0.4991 in sets s_0, s_3 and s_4 credit ratings are equal to zero because there is no intersection of the score 0.4 and these sets. By this way, the credibility level of 0.4991 is distributed into the proper credit ratings with the calculated belief degrees.

Table 7
Belief degrees of Company 13.

Criteria	Scores	Belief Degrees				
		s_0	s_1	s_2	s_3	s_4
x_1	0.4991	0.0000	0.5058	0.4942	0.0000	0.0000
x_2	1.0948	0.0000	0.0000	0.8506	0.1494	0.0000
x_3	1.9819	0.0000	0.0000	0.4819	0.5181	0.0000
x_4	0.8666	0.0000	0.0000	0.0000	0.6993	0.3007
x_5	0.0128	0.0000	0.0000	0.0000	0.0000	1.0000
x_6	0.0516	0.0000	0.0000	0.5717	0.4283	0.0000
x_7	0.1969	0.0000	0.0000	0.0000	0.0000	1.0000
x_8	0.0204	0.4689	0.5311	0.0000	0.0000	0.0000
x_9	0.0270	0.0000	1.0000	0.0000	0.0000	0.0000
x_{10}	0.0071	0.0000	0.9420	0.0580	0.0000	0.0000
x_{11}	0.0655	0.4760	0.5240	0.0000	0.0000	0.0000
x_{12}	0.1783	0.0000	0.0000	0.9620	0.0380	0.0000

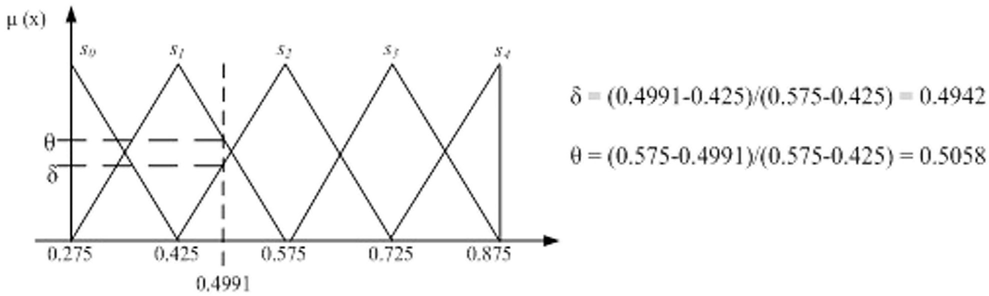

Fig. 5. Belief degrees calculation example.

$\beta_{1,13,0} = \mu_{s_0}(0.4991) = 0$ (there is no intersection of s_0 and 0.4991 line)
$\beta_{1,13,1} = \mu_{s_1}(0.4991) = 0.5058$ (θ in Fig. 5);
$\beta_{1,13,2} = \mu_{s_2}(0.4991) = 0.4942$ (δ in Fig. 5);
$\beta_{1,13,3} = \mu_{s_3}(0.4991) = 0$ (there is no intersection of s_3 and 0.4991 line);
$\beta_{1,13,4} = \mu_{s_4}(0.4991) = 0$ (there is no intersection of s_4 and 0.4991 line).

As a result, belief structure of Company 13 for criterion 1 can be formed as: $B_{13}(I_1) = \{(0.5058, s_1), (0.4942, s_2)\}$.

Considering the scores of Company 13 in all the criteria and triangular fuzzy numbers defined for the criteria, the related belief degrees are calculated similarly and presented in Table 7.

Furthermore; belief structures of the performance of all companies with respect to all criteria were also calculated. Please see Attachment 1 for all the belief degrees.

5.3.3. Calculation of cumulative belief degrees

The CBDs of the companies' performance on the criteria were calculated using Eq. (7). For illustration purposes, CBDs related to the company 13 are presented in Table 8. For instance, for the first criterion CBDs were calculated as follows:

$$\gamma_{1,13,0} = \beta_{1,13,0} + \beta_{1,13,1} + \beta_{1,13,2} + \beta_{1,13,3} + \beta_{1,13,4} = 0 + 0.5058 + 0.4942 + 0 + 0 = 1$$
$$\gamma_{1,13,1} = \beta_{1,13,1} + \beta_{1,13,2} + \beta_{1,13,3} + \beta_{1,13,4} = 0.5058 + 0.4942 + 0 + 0 = 1$$
$$\gamma_{1,13,2} = \beta_{1,13,2} + \beta_{1,13,3} + \beta_{1,13,4} = 0.4942 + 0 + 0 = 0.4942$$
$$\gamma_{1,13,3} = \beta_{1,13,3} + \beta_{1,13,4} = 0 + 0 = 0$$
$$\gamma_{1,13,4} = \beta_{1,13,4} = 0$$

As a result, the CBD structure for the first criterion of Company 13 was $C_{13}(I_1) = \{(1, s_0), (1, s_1), (0.4942, s_2), (0, s_3), (0, s_4)\}$. The last row of Table 8 represents the aggregated CBDs that are explained in the next step.

5.4. STEP 4. Specifying Credit Ratings

5.4.1. Aggregation of cumulative belief degrees

In order to determine the credit ratings of the companies, the CBDs of criteria were aggregated using Eq. (15). For instance, for the company 13, CBD at s_1 level was calculated as follows:

Table 8
Cumulative belief degrees of the Company 13.

Criteria	Weight of criteria	Cumulative Belief Degrees				
		s0	s_1	s_2	s_0	s_4
x_1	0.2137	1.0000	1.0000	0.4942	0.0000	0.0000
x_2	0.0676	1.0000	1.0000	1.0000	0.1494	0.0000
x_3	0.0250	1.0000	1.0000	1.0000	0.5181	0.0000
x_4	0.0466	1.0000	1.0000	1.0000	1.0000	0.3007
x_5	0.0338	1.0000	1.0000	1.0000	1.0000	1.0000
x_6	0.0730	1.0000	1.0000	1.0000	0.4283	0.0000
x_7	0.0454	1.0000	1.0000	1.0000	1.0000	1.0000
x_8	0.0861	1.0000	0.5311	0.0000	0.0000	0.0000
x_9	0.1865	1.0000	1.0000	0.0000	0.0000	0.0000
x_{10}	0.0673	1.0000	1.0000	0.0580	0.0000	0.0000
x_{11}	0.1217	1.0000	0.5240	0.0000	0.0000	0.0000
x_{12}	0.0333	1.0000	1.0000	1.0000	0.0380	0.0000
$C_{13}(I)$		1.0000	0.9017	0.4343	0.1814	0.0932

$$\gamma_{13,1} = \sum_{k=1}^{12} w_k \gamma_{13,k1} = 0.2137 \times 1 + 0.0676 \times 1 + 0.0250 \times 1 + 0.0466 \times 1 + 0.0338 \times 1 + 0.0730 \times 1 + 0.0454 \times 1$$
$$+ 0.0861 \times 0.5311 + 0.1865 \times 1 + 0.0673 \times 1 + 0.1217 \times 0.5240 + 0.0333 \times 1 = 0.9017$$

All the other aggregated CBDs (for the credit ratings of s_0, s_2, s_3 and s_4) are calculated as given above. As a consequence, the credit rating of Company 13 structured in CBDs is given in the last row of Table 8. According to the result, the company's credit risk is concentrated between D (s_1) and C (s_2). So its credibility could be accepted as providing lower confidence for the assignation of a higher credit limit. At the same time, the company had many risk components. The credit analyzer should be aware of this situation and monitor the company closely. When similar calculations were made for the other companies, the results presented in Table 9 were found.

5.4.2. Specifying a single rating for each applicant

At the final stage, a single credit rating for each company was specified based on the CBDs calculated in the previous stage. The resulting credit ratings for different threshold values ($\tau = 0.5$, $\tau = 0.7$, $\tau = 0.3$) are presented in Table 9. For instance, the credit rating of Company 13 for $\tau = 0.5$ was calculated using Eq. (16) as follows:

$$R_{13}^{0.5} = \underset{i=0,\dots,4}{\text{Sup}} \left[s_i | \gamma_{13i} \geq 0.5\right] = \text{Sup}[s_0, s_1] = s_1$$

In this example, s_1 was the highest linguistic term that had a CBD more than or equal to 0.5. Therefore, the rating given was D. On the other hand, when $\tau = 0.3$, its rating increased to C.

As stated in Section 4.4, it is expected that a risk avoiding lender should prefer a threshold that is larger than 50% and conversely, a risk seeker lender should select a threshold value that is less than 50%. The first lender takes less risk by assigning lower credit ratings in this situation and the second type of lender prefers more risk by assigning higher credit ratings than a neutral lender would.

In Table 10, results of the analysis considering threshold values 0.3, 0.5 and 0.7 are demonstrated. It is seen that when the threshold value is increased (from 0.3 to 0.7) the number of companies at the level of higher credit ratings (A and B) decreases and number of companies at the level of lower credit ratings (D and E) increases. It is evident that the companies with higher credit

Table 9
Credit ratings of the selected companies.

Companies	CBDs					Credit Rating		
	s_0	s_1	s_2	s_3	s_4	Risk neutral $\tau = 0.5$	Risk avoiding $\tau = 0.7$	Risk seeker $\tau = 0.3$
Company 1	1.0000	0.6195	0.4767	0.4532	0.3703	s_1 – D	s_0 – E	s_4 – A
Company 9	1.0000	0.4392	0.4259	0.4259	0.3687	s_0 – E	s_0 – E	s_4 – A
Company 13	1.0000	0.9017	0.4343	0.1814	0.0932	s_1 – D	s_1 – D	s_2 – C
Company 27	1.0000	0.7265	0.4488	0.3963	0.3035	s_1 – D	s_1 – D	s_4 – A
Company 34	1.0000	0.8540	0.8090	0.5331	0.4256	s_3 – B	s_2 – C	s_4 – A
Company 47	1.0000	0.6281	0.6246	0.5900	0.5494	s_4 – A	s_0 – E	s_4 – A
Company 51	1.0000	0.7728	0.5175	0.3893	0.0667	s_2 – C	s_1 – D	s_3 – B
Company 56	1.0000	0.6000	0.5574	0.5144	0.4902	s_3 – B	s_0 – E	s_4 – A
Company 62	1.0000	0.6566	0.5216	0.3877	0.2663	s_2 – C	s_0 – E	s_3 – B
Company 63	1.0000	0.9597	0.6108	0.2576	0.0432	s_2 – C	s_1 – D	s_2 – C

Table 10
Number of companies in credit ratings for different threshold values.

Credit rating	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$
s_4 (A)	29	2	0
s_3 (B)	12	3	0
s_2 (C)	15	20	1
s_1 (D)	6	28	7
s_0 (E)	2	11	56

ratings move to lower ones. In the analysis considering 0.3 threshold, the number of companies having rating A is 29 but this value decreases to 0 while the threshold is set at 0.7. At the same time, the number of companies having rating E is 2 when the threshold value is 0.3 but this number increases to 56 when the threshold is 0.7. The risk attitude of the lender is changing from risk seeker to risk avoider when the threshold is changed from 0.3 to 0.7. This means that the risk appetite of the lender, which causes this difference, decreases when the threshold value increases.

One of the original parts of this paper is its credibility assessment approach which determines a credit rating distribution for each applicant by utilizing CBDs ascertained for each rating class. In other words, an applicant's credibility is measured and symbolized by a distribution of credit rating and it additionally can provide a single credit rating for the needs of today's banking industry. It is expected to provide more information for credit analyzers in this manner. For example, Company 13 has a bigger CBD value in rating D and E. It has a CBD of 0.9017 representing a credibility assessment belonging to credit rating D and higher. At the same time, it can be said that it has (0.4343–0.1814 =) 0.2529 credibility in the C level rating. Besides, its CBD values are smaller for the first two ratings (B and A) and the accumulation of CBDs does not belong to any of them.

The bank may create any kind of rule set for assigning credit limits, payment period, collateral or any kind of obligations by utilizing these credit rating distributions. The companies holding different CBDs for each credit rating may encounter different liabilities. For example, if a company, independently from its assigned credit rating, has a CBD that is greater than 0.70 in rating D, it may be responsible for providing more indemnification. This rule based system will reduce the workloads of credit analyzers because they are responsible for restoring each applicant's performance scores one by one in the current banking systems, regardless of their determined credit rating. It follows that none of these recommendation possibilities is available within the single credit rating determination systems.

6. Effect of social media data in credit rating

We consider the data provided by social media in the credit rating problem. In this section, we have analyzed the effect of using social media data by comparing the credit rating results obtained through with social media and without social media. This comparison is based on the assigned credit ratings of the companies and the results are summarized in Table 11. These results were obtained for threshold value 0.5. Table 11 (a) presents the credit rating migration matrix between the two situations and Table 11 (b) shows the number of companies determined for each rating deterioration or improvement degree.

As seen from Table 11, 32 companies (50.0%) kept their credit ratings while the credit ratings of the other half changed when

Table 11
The comparison results.

(a)

		With SM					
		A	B	C	D	E	
Without SM	A	*1*	2	4	2		9
	B	1	*1*	10	2	1	15
	C			*5*	4		9
	D			1	*15*		16
	E				5	*10*	15
		2	3	20	28	11	

(b)

	Number of Companies	Ratio of Companies	
Decrease by 3 ratings	3	4.7%	39.1%
Decrease by 2 ratings	6	9.4%	
Decrease by 1 rating	16	25.0%	
No Change	32	50.0%	
Increase by 1 rating	7	10.9%	10.9%
Total	64		

social media data is considered. This means that considering social media in credit rating was important for half of the investigated companies. The direction of the change while considering social media is negative because the ratings of most of the companies decreased: 25.0% of the companies had one degree decrease; 9.4% of them had two degrees decrease; and 4.7% had three degrees decrease. Besides, seven companies (10.9% of all) improved their rating by one degree. In accordance with [34], it is found that the micro blog sites like Twitter are accepted by users as a complaint platform where they share mostly negative emotions and the situations which they are dissatisfied with. As a result, the Twitter criteria mostly decreased the credit ratings of companies due to the negative tendency of shared information on Twitter.

The total importance of social media criteria is 15.50% which is lower than the total importance of financial criteria (84.50%). The case study which are explained above shows that social media consideration has an impact on the credit ratings of 32 companies in our data set. This finding emphasize that the importance of social media can be smaller but it generates a remarkable difference. As suggested by Wei et al. [38], social media have the opportunity of being utilized in credit rating issue. Additionally, social media consideration in evaluating a company's credibility level can be very useful because assessments of financial or non-financial criteria can sometimes be unreliable or the credit analyzers' perception or his/her personal expedience can create a manipulative impact. Social media's customer oriented context may be advantageous to deal with this manipulation possibility.

7. Conclusions

In this study, a new multiple criteria approach is proposed for credit rating. Different from existing methods like artificial intelligence, data mining, discriminant analyses, etc., the proposed approach aims to introduce the social media criteria as a support for non-financial assessment of the credit rating process and has a different representation style of credit ratings, namely CBDs. In this respect, it is intended to create broader interpretation possibilities for credit analyzers.

The first contribution of this paper is a new approach for credit rating that allows the use of different sources such as financial, non-financial and social media data, while assigning credit ratings to companies. All data sources are transformed to belief degrees without losing any information. Aggregation operators are defined to find final rating of companies with credibility distributions. This approach is particularly useful when some required information of companies (such as non-financial data sources in the case study) is not available to make sound decision related to applicant companies.

The second contribution is the consideration of social media data in a credit rating approach. By this way, we introduced a new source of information that may be used when financial and/or non-financial data are not sufficient enough to make decisions regarding the creditability of a company. In order to process the social media data, SA, which is fundamentally a machine learning based methodology, is utilized. Because of its popularity and easiness of acquiring data, Twitter was chosen as the source of social media data.

The third contribution of the paper is the representation of credit ratings as the distribution of CBDs. A company's credibility is represented by a credibility distribution among all the credit ratings instead of a single credit rating. By this way, it provides more information for credit analyzers. For example, a bank may create any kind of rule set for assigning credit limits, payment period, collateral, or any kind of obligations considering the proposed credit rating distribution approach. The companies with different CBDs for each credit rating may encounter different liabilities. This rule based system will reduce the workloads of credit analyzers who are responsible for monitoring and restoring each applicant's performance scores. This kind of intelligent decision tool will provide an interception for human error or the possibility of manipulation. None of these recommendation possibilities is available in the single credit rating approaches. This is therefore the major contribution of our proposed methodology to the field of credit rating.

For the banking system's current requirements, the bank as a lender needs an exact credit rating for an applicant. In this study, credit ratings of the companies represented by CBDs are transformed to a single credit rating based on a threshold value. The single rating enables us to conduct a comparison analysis in order to determine the influence of social media within the credit rating process. According to the results, it is found that social media effectiveness is important for half of the companies investigated. The direction of change is negative because most of the companies' rating decreased to lower credit ratings. This is mainly due to the fact that the microblog sites like Twitter are used as a complaint platform mostly sharing negative emotions and reports of situations which caused dissatisfaction. This fact should be considered while benefitting from social media data in credit rating approaches.

On suggesting such a new method, we are aware of the necessity of comparing the results with the current ones. However, it is impossible to get any information from banks or financial institutions related to their method or the data they use. The banking regulations of Turkey government forbade the sharing of the customer data even if they were anonymized. Because of the regulations, the bank managers do not give information related to the current rating methods even for the scientific purposes. Therefore, we could not realize a comparative analysis of our method. In a future study, the validation process regarding the prediction power of the proposed method can be conducted if required information is provided.

In terms of international and national legislations and banking laws, banks or other institutions requiring credit ratings operations may be in need of a probability of default measurement which is calculated based on some statistical methods. A possible further research can be conducted by researching of procedures focusing on transformation of the proposed method's CBDs to probability of default. Secondly, adding the non-financial criteria into the current methodology will strengthen the rating decision. Finally, software can be developed for facilitating the calculations and providing a widespread usefulness and it may gain wider scope as an assessment technique for other types of problem involving risk measurement.

Acknowledgments

This work was supported by Istanbul Technical University BAP [grant number 38818]. Additionally, Sait Gül has been beneficiary of The Scientific and Technological Research Council of Turkey (TÜBITAK) scholarship programme (scholar id: 1649B031200042) since 2012.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.datak.2018.05.005.

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