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Feed Forward Neural Network (FFNN) approach for evaluating business potential of intellectual properties

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Abstract

Artificial Neural Networks (ANN) has been phenomenal in predictive analytics of business problems. This study paved to compute business potential of individual patents using Feed-Forward-Neural Network algorithm to predict the likelihood of a patent to survive until its maximum expiration date. The binary classification is named as Core-Business-Patents (CBPs) and Non-Core-Business-Patents (Non-CBPs). This project aimed to aid businesses identifying their business potential of intellectual properties, because patents are retained when profits created are larger than the maintenance fee, finding emerging technologies of competitive firms. A total of 31 indicators and maintenance fee data was used for learning a FFNN model. Consequently, Recall was higher than Precision in every patent, therefore F2-Measure is considered as evaluation metric.

Keywords

Neural Network | Predictive Analytics | Google Colab | Patent | Patent evaluation

Introduction

Business analytics refers to methods and practices that create values through data for individuals, firms and organizations. This field is experiencing a radical shift due to the advent of deep learning: deep neural networks promise improvements in prediction performance as compared to models from traditional machine learning. In this study, employs to use past data and attempts to evaluate business potential of an individual patent by predicting the likelihood because they have a greater expectation to create direct or indirect profit throughout their entire lifetime. To this end, this study uses machine-learning-based model with multiple patent indicators that can be defined immediately after a patent is filed. Specifically, a total of 24 internal/environmental indicators were extracted from patent data. Next, Feed Forward Neural Network Model was employed to predict the likelihood that a patent will survive until its maximum expiration date. According to the results, apparent trend was exhibited in which the recall is higher than the precision and F2 Measure is considered as evaluation metric. The principal advantage of our approach for evaluating the business potential of a patent quantitatively is its wide applicability. Because this approach does not depend on lagging indicators, in contrast with prior studies, it can be applied to newly filed patents with little or no forward citation information. Consequently, results would aid businesses to uncover hidden major technologies of high business potential and enable firms to establish tactical decisions in business strategy and R&D planning.

Literature Review

Patent holders maintain exclusive rights to their patents by paying expensive maintenance fees, there is some indication that the lifetime is closely coupled with a patent's business potential or economic value. Indeed, according to empirical studies, the lifetime of a patent has a strong relationship with its value and is therefore frequently used as a proxy estimate of the patent's quality in terms of its business potential (Guellec & de la Potterie, 2000). That is, the longer a patent survives after its first filing date, the more likely the patent is to create a direct or indirect business value (Pakes,1984). Specifically, the patent holders can directly profit by developing existing technologies or products faster than their competitors based on their patents (Lemley & Shapiro, 2006), while indirectly benefiting from a hindrance in the business operations of their competitors within the market value where the patent is applied (Bader, Gassmann, Ziegler & Ruether, 2012). Machine learning-based approaches have recently been used to analyze the value or quality of a patent from perspectives other than the lifecycle, e.g., the evaluation of the monetary legal value of a patent infringement lawsuit data (Lai & Che, 2009) and the evaluation of the quality of a patent from the perspective of the patent transferability (Trappey, Trappey, Wu, & Lin, 2012).

OCGPDT patent definition:

According to Office of the Controller General of Patents, Designs & Trademarks, a patent holder must pay a maintenance fee immediately after approval to retain exclusive rights to the patent. Once a patent is granted and its first maintenance fee is paid, three additional maintenance fee payments with a grace period of twelve months are required; these must be paid within every year until its maximum expiration period. If the maintenance fee of a patent is not paid during the payment period, the patent expires and the exclusive rights of the patent holder over the patent ends. If the patent holders do not pay the maintenance fee within any given period, they must pay a surcharge. If a patent expires because a fee has not been paid within its designated period, the patent right can be recovered by filing a petition with the USPTO to prove that there was no intent to miss the payment. The maintenance fee varies according to the type of applicant, the number of claims included, and the payment term (Table 1)

Table 1*:*

On what payable	For e-filing			For physical filing		
	Natural person(s) and/ or Startup	Small entity, alone or with natural person(s) and/ or Startup	Others, alone or with natural person(s) and/ or Startup and/ or small entity	Natural person(s) and/ or Startup	Small entity, alone or with natural person(s) and/ or Startup	Others, alone or with natural person(s) and/ or Startup and/ or small entity
2	4	5	6	7	8	9
	Rupees	*Rupees*	*Rupees*	*Rupees*	*Rupees*	*Rupees*
On application for a patent accompanied by provisional or complete specification	1600	4000	8000	1750	4400	8800
	Multiple of 1600 in case of every multiple priority.	Multiple of 4000 in case of every multiple priority.	Multiple of 8000 in case of every multiple priority.	Multiple of 1750 in case of every multiple priority.	Multiple of 4400 in case of every multiple priority.	Multiple of 8800 in case of every multiple priority.
For each sheet of specification in addition to 30, excluding sequence listing of nucleotides and/ or amino acid sequences	160	400	800	180	440	880
For each claim in addition to 10;	320	800	1600	350	880	1750
For each page of sequence listing of nucleotides and/ or amino acid sequences	160 subject to a maximum of 24000	400 subject to a maximum of 60000	800 subject to a maximum of 120000	Not allowed	Not allowed	Not allowed

Methodology:

In this study, a machine-learning based approach to predicting the likelihood that a patent will survive until its maximum expiration date is proposed for evaluating the business potential of a patent. Specifically, the proposed approach involves four steps: (1) constructing a patent database and collecting patents with a determined lifetime, (2) defining and extracting multiple patent indicators, (3) predicting the likelihood that a patent belongs to the set of core business patents (CBPs), and (4) evaluating the business potential of patent.

Indicators for CBPs and Non-CBPs:

The indicators are divided into internal and environmental indicators where internal indicators are considered as indicators that affect patent lifetime and environmental indicators are chosen because of rapidly changing patented technology.

Internal Indicators related to patent lifetime:

Specifically, a total of 19 inherent indicators, which can be categorized into (1) the technical scope (2) priority range (3) geographical scope, (4) co-operation degree, and (5) completeness.

(i) Technical Scope of a patent: This subcategory contains a total of six indicators addressing the technical scope of a patent. First, based on bibliographic information, the number of words in the full text of the patent, the number of dependent claims, the number of independent claims, and the average number of words per independent claim are selected as variables indicating the degree of the detailed technical scope and the specificity of the patent. In particular, the claims of a patent are divided into two types: independent and dependent claims. An independent claim of a patent does not depend on other claims and thus describes the content of the most fundamental knowledge regarding the invention of the patent, whereas a dependent claim specifies the details of the cited independent claim and provides extended information. Information from the International Patent Classification (IPC) can also be indicative of the technology fields (Zhang et al., 2016) because the IPCs that a patent belongs to are naturally closely coupled with the technical scope of the patent.

(ii) Priority range of a patent: The priority of a patent refers to the right of an applicant who filed the patent application to subsequently file a later application for the same invention as if the latter application was filed on the same date as the former application; for regular applications, this priority is valid for a certain period.

The competitiveness and direction of a patent portfolio were studied by constructing a network using the patent priority and citation information. As a basic concept in the building of patent family relationships, priority was deemed to be essential in the framework for the design of new products. Therefore, the number of priorities and the number of priority nations are used to reflect the priority range of a patent.

(iii) Geographic scope of a patent: To reflect the geographical scope of a patent, this approach mainly uses family information of the patent. Here, the patent family refers to a set of patents filed in several countries, while sharing one or more common countries. Therefore, the family size of the patent is expressed as the number of patent offices that protect the patents, namely, the number of countries in which the patents have been filed. Based on the cited literature, the number of domestic family patents, the number of foreign family patents, and the number of family patent nations are appended to the indicator of the geographical scope.

(iv) Cooperation degree of a patent: In this subcategory, the present approach uses the number of applicants, the number of foreign applicants, the number of applicant nations, and the number of assignees to determine the degree of cooperation of a patent.

(v) Completeness of a patent: This subcategory comprises a total of four indicators, namely, the number of backward citations, the number of changed claims, the grant time lag, and the number of abstract words to reflect the completeness of a patent. In addition, the grant time lag of the patent, namely, the interval between its filing date and issuance date, is used. A patent applicant must usually wait during the patent examination period conducted by patent officers. Thus, a long-term review implies that the patent applicant has put a great deal of effort into researching and inventing its patent.

Environmental indicators: Environmental indicators related to patent lifetime Because the environment of a patented technology is rapidly changing, affecting the decision making involved in patent registration and technology strategies, environmental indicators have been used to reflect such changes in the technology fields to which a patent belongs. To this end, this study also selects a total of twelve environmental indicators, namely, the IPC activity, IPC size, IPC competitiveness, IPC sections (8), and average gap of the backward citations. In addition, eight IPC section indicators are used, the values of which are 1 when a patent belongs to each IPC section from A to H, and are 0 otherwise, which serve as indicators for the business potential of the patent. To determine the changing speed of the related technology fields in terms of backward citation information, this approach uses the average gap of backward citations.

Implementation:

Data Collection:

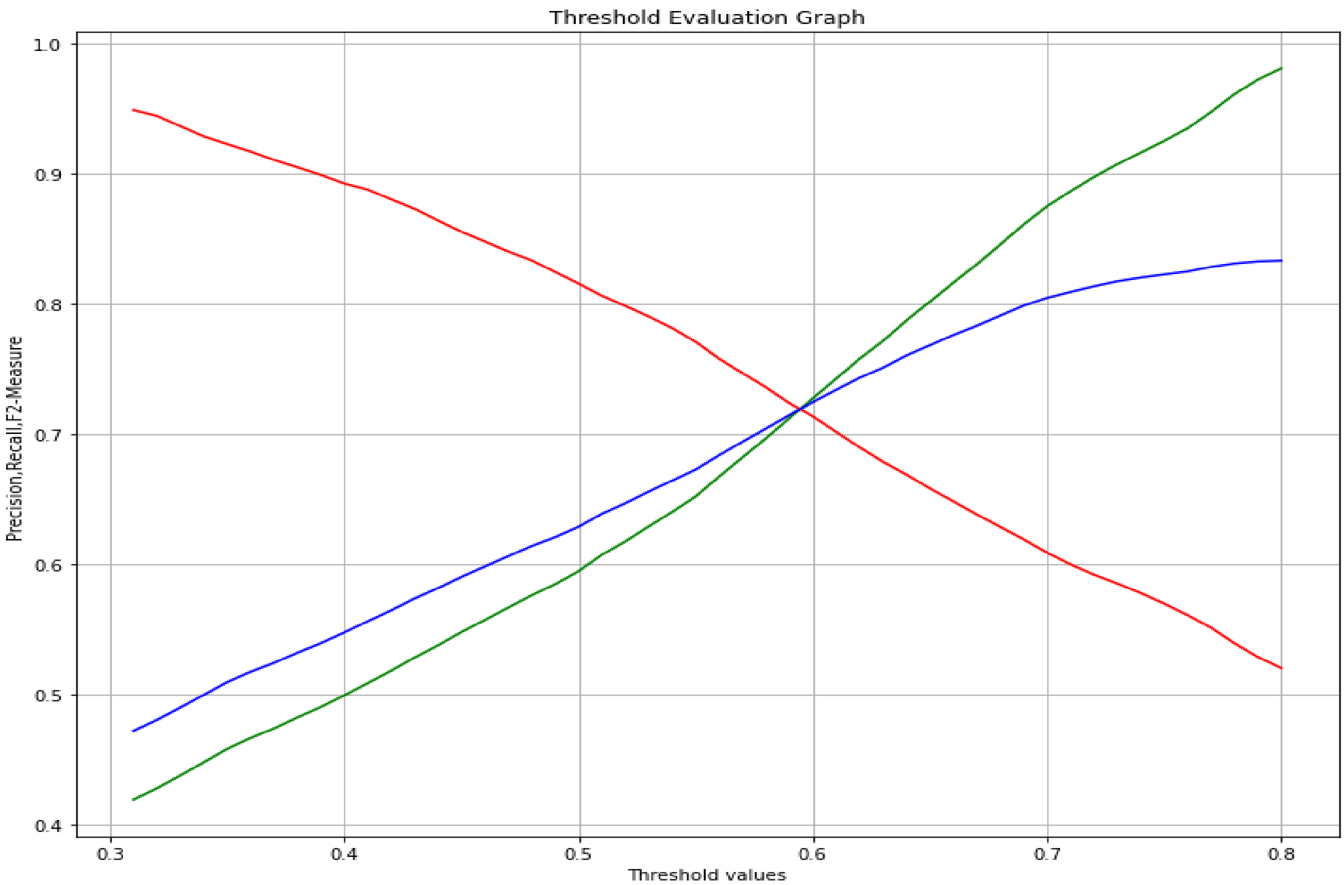
The dataset for this project was collected from www.elsevier.com, where dataset consisted of 2,00,000 data points in csv form. It consisted of 35 columns defining indicators for computing the business potential and classifying into CBPs and Non-CBPs. In addition, 150 datapoints additionally were collected from http://ipindia.gov.in/e-gateways.htm#public-search.

Neural Network Learning:

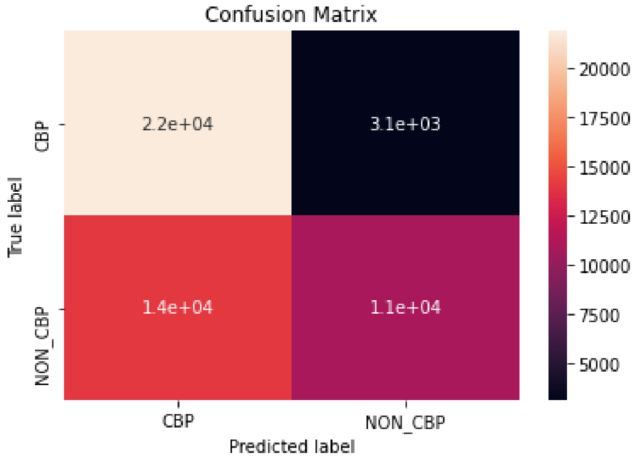
The dataset was divided to training dataset and test dataset, training dataset consisted of 1,50,100 examples and test dataset consisted of 50,050 examples. In this step, an FFNN model was built using the training dataset and learned on the Google Colab with GPU runtime. The model trained for 2,500 epochs and batch size of 512 examples. It should be noted that this approach attempted to increase the F2-measure owing to its goal of identifying CBPs that have the potential to create a business value through retainment. That is, the recall value is considered more important than the precision value because a false negative rate is more critical than a false discovery rate in a practical business environment. In addition, a stratified sampling method was applied to divide the population into layers and evenly select the samples by year. Moreover, this approach used a rectified linear unit function as an activation function of the hidden layers and a cross-entropy function, which is mainly applied as a loss function in a classification problem. To prevent the trained model from overfitting, the hidden dropout ratios were set to 0.5, and a mini batch was applied to the model such that the input data used in each learning cycle learn from a training set of 128 observations. Next, this approach cautiously determined the number of layers and the number of nodes in a layer, which depends on the size and nature of the dataset. Generally, a single hidden layer can approximate continuous functions and so we first tested the performance by adjusting the number of nodes for three hidden layers. Table 8 shows the precision, recall, and F2-measure according to the numbers of nodes and hidden layers. The approach described herein attempted to find the model with the best F2-measure, following Covington's approach (Covington et al., 2016), which weighed the recall higher than the precision.

Results:

In this step, the business potential of a patent was evaluated based on the prediction result regarding the likelihood that a patent survives until its maximum expiration date. this approach adjusted the threshold t of the patent's business potential value to address the business potential from various viewpoints. Indeed, the performance of a decision system can be analyzed from multiple viewpoints by adjusting the threshold for determining the positive/negative state of a predicted value. This graph shows the variance of the precision recall and F2-Measure.



Therefore, in this study, the evaluation results were analyzed by adjusting the threshold and calculating the number of expected CBPs and the performance of the recall, precision, and F2-measure for each threshold. As the threshold value c increases, the model likely becomes pessimistic, and therefore patents tend to be expected to be CBPs. In particular, when the threshold value was set to 0.7, 22,188 patents belonged to the expected CBPs. In addition, the precision, recall, and F2-measure were 60.6%, 87.1%, and 80.4%, respectively, at the same threshold. The reason why the recall value rapidly decreased as the threshold value gradually increased from 0.7 to 0.5 is the model predicts fewer patents as being CBPs with a high business potential. The F2-measure also decreased as the threshold decreased, whereas the precision value increased in proportion to the threshold value. Clearly, however, the precision value is relatively lower than the recall for all thresholds.



In the confusion matrix of the validation set, there are 22,188 patents in the true-positive (TP) category, meaning that they were retained until their maximum lifetime. In terms of the false-positive (FP) category, there are 14,087 patents that were not maintained but were expected to be retained until their maximum lifetime, whereas the false-negative (FN) category includes 3,125 patents that were not held for their maximum lifetime but were determined by the model to be non-CBPs. The true-negative (TN) category refers to patents that were abandoned before they reached their maximum lifetime but were deemed to be CBPs

Expected CBPs on multiple thresholds:

	Threshold values					
	0.5	0.55	0.65	0.70	0.705	0.71
CBPs	15,562	16,256	20,562	22,188	22,656	22,896
Precision	81.53%	77.06%	65.80%	60.87%	60.38%	59.71%
Recall	59.44%	65.18%	80.14%	87.46%	87.98%	88.62%
F2 Measure	62.84%	67.25%	76.79%	80.40%	80.60%	80.89%

Discussion:

Based on the results of the present study, this chapter describes how to apply the proposed approach in practice, provides a careful interpretation of the results, and discusses the use of only leading indicators, which is a principal advantage of the proposed method.

The proposed approach evaluates the business potential of a patent by predicting the likelihood that the patent will survive until its maximum expiration date. Because the proposed approach employs patents from entire technology areas for training and does not use lagging indicators, including forward citation information, there are a wide range of possible applications such as in anticipating emerging technologies, monitoring macro technology trends, and conducting a competitive analysis. First, the proposed approach can assess the business potential of newly issued patents without their forward citation information at a relatively early time during their lifecycle. Furthermore, based on the evaluation of such patents, this approach can identify pre-emerging technology fields in which many patents with high business potential have been recently issued, and in which the possibility of new technologies emerging in the near future is high. As such, the applicability of this approach to newly issued patents is a clear difference from prior studies, which have depended on lagging indicators and analyzing patents whose value has already been determined. Next, the proposed approach can be applied in monitoring macro technology trends in real time by analyzing the time-varying business potential of a technology field. Specifically, based on the evaluation result of patents belonging to a particular technology field, the number of expected CBPs in a technology field or the average business potential value of patents can be calculated in real-time, and a time-series analysis of such results is also possible. Finally, the proposed approach can provide quality competitive intelligence by analyzing the patents of a competitive firm in terms of their business potential. Specifically, by identifying their expected CBPs and hidden major technologies with a high business potential, the technological strategy of such businesses can be determined based on their strengths and weaknesses. Therefore, the proposed approach can enable a firm to preempt a technology with a high business potential and establish tactical decisions in its business strategy or R&D planning.

Analyzing the performance of this approach carefully, an interesting trend can be seen in which the recall is higher than the precision regardless of the threshold value or model used. That is, there are some patents that were deemed to have a high business potential according to their evaluation but were abandoned before their maximum lifetime. This approach focused on such an observation and found the reason why the precision is lower than the recall from studies conducted on patent maintenance. According to the literature, surprisingly, 50%–60% of patents are abandoned because the patent holder is unable to pay the maintenance fee, even if such patents have a significant business value. Consequently, this study can conclude that the high FP value of the model used supports the findings of the literature. In addition, those patents that the model regards as CBPs are defined as patents expected to retain their sufficiently high business potential until their maximum lifetime. The relatively low precision values are also acceptable, since the proposed approach address decision making of maintaining patents under business environment with high uncertainty. In the same vein, the approach can be used to filter out fewer valuable patents at an early stage in a real-life business environment, considering the performance and sufficient interpretation.

Conclusion:

This study proposed a novel approach based on an FFNN model to predict the likelihood that a patent survives until its maximum expiration date. This study focused on such a long-surviving patent because such a patent is expected to create direct or indirect profit throughout its entire lifetime. this study evaluated the business potential of individual patents from the viewpoint of patent lifetime. The proposed approach outputs its evaluation results regarding a business potential as a value between zero and 1, and thus the output values can be converted into various useful forms of information, including a business potential grade and expected CBPs. For example, these results can be used in pre-detecting emerging technologies, monitoring technological trends, and providing competitive technology intelligence. Consequently, the proposed approach can efficiently support experts in their judgment of a patent valuation by providing a quality evaluation. In addition, small and medium-sized enterprises or individual applicants can grasp the business potential of new or existing patents that they possess, and thus will be able to conduct intellectual property financing activities such as patent transactions or loyalty licensing more effectively. This approach can also allow a major corporation or national organization to comprehend the CBPs in any technology field and even in new or emerging technologies that are not yet mature enough to evaluate, thereby enabling them to recognize key applicants or inventors in such fields. In addition, linking expected CBPs with products and selecting key patents for each of the products will make it possible to determine the business potential, technical completeness, performance, and marketability of each product.

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