2003 BELTWIDE COTTON CONFERENCES, NASHVILLE, TN – JANUARY 6-10

DATA MINING APPROACHES IN OPTIMIZATION OF COMBED YARN PROCESSING

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Abstract

Neural networks algorithms are among the most popular data mining and machine learning techniques used today. As computers become faster, the neural net methodology is replacing many traditional tools in the field of knowledge discovery and some related fields. Neural networks tools are now used by many project engineers because - unlike most competing algorithms - the neural networks extrapolation does not require the mathematical model. We can perform the neural networks prediction without knowing what are the formulas, or laws. In this work we will use data mining technologies to strength the power of the preparation of the database and "neural networks" to extract "hidden" information from the 2001 Uster Statistics and textile spinning database. The goal of this study is to show how it is important the application of the data mining techniques namely neural networks in the optimization of combed yarn processing. The neural networks analysis will be used to develop non-linear predictive models that would better explain the relationships between the yarn specifications, than the classical statistical methods.

Introduction

The rapid emergence of electronic data processing and collection methods has leaded some to call recent times as the "Information Age". However, it may be more accurately termed as "The age of data glut".

These databases contain so much data that it becomes very difficult to understand what that data is telling us. There is hardly a transaction that does not generate a computer record somewhere. All this data has meaning with respect to better understanding customer needs and preferences.

But how do we discover those needs and preferences in a database that contains gigabits of seemingly incomprehensible numbers and facts. Data mining does just that. However, used blindly, incorporation of data mining techniques can result in large expenditures of money and time to no avail. The key issue is how to avoid frustrating and costly mistakes and improve engineering process by correct use of these powerful methods.

Statistical methods have long been used to extract information from data. Multifactor analysis of variance and multivariate analysis include statistical methods that could identify the relationships among factors that influence one characteristic or one process.

One of problems with these approaches is that the techniques tend to focus on tasks in which all the attributes have continuous or ordinal values. Many of the attributes are also parametric, that is, they assume a particular probability distribution of the variables. Many methods also assume that a relationship is expressible as a linear combination of the attribute values. Statistical methodology also very often assumes normally distributed data - a sometimes tenuous supposition in the real world. These assumptions are not usually verified in practice and therefore the results are questionable.

Data mining techniques discover more information that the factors that influence this characteristic or process.

Even some sophisticated artificial intelligence based tools that use case-based reasoning, a nearest neighbor indexing system, fuzzy (continuous) logic, and genetic algorithms don't qualify as data mining tools since their queries also originate with the user. Certainly the way these tools optimize their search on a data set is unique, but they do not perform autonomous data discovery. Neural networks and decision tree methods on the other hand, do qualify as true automatic data mining tools because they autonomously interrogate the data patterns.

Neural networks are one of the most established data mining technologies in use. It is what can be termed data driven modeling in that a process goal is defined and used to generate patterns that relate to that process goal. The process goal can be the occurrence of an event such as "influence of the count in the unevenness of a yarn" or the magnitude of an event such as "yarn tenacity" or the "unevenness".

Data Mining and Neural Networks

Data mining involves the semi-automatic discovery of patterns, associations, changes, anomalies, rules, and statistically significant structures and events in data. In other words, data mining attempts to extract knowledge from data.

Data mining differs from traditional statistics in several ways: formal statistical inference is assumption-driven in the sense that a hypothesis is formed and validated against the data. Data mining in contrast, is discovery driven in the sense that patterns and hypothesis are automatically extracted from large data sets. Further, the goal in data mining is to extract qualitative models, which can easily be translated into patterns, logical rules or visual representations. Therefore, the results of the data mining process may be patterns, insights, rules, or predictive models that are frequently beyond the capabilities of the best human domain experts.

The neural networks are one of the most popular technique method used in data mining. The area of neural networks probably belongs to the borderline between the artificial intelligence and approximation algorithms. Think of it as of algorithms for "smart approximation".

The neural networks are used in (to name few) universal approximation (mapping input to the output), tools capable of learning from their environment, tools for finding non-evident dependencies between data and so on.

The neural networking algorithms (at least some of them) are modeled after the brain and how it processes the information. The brain is a very efficient tool. Having about 100,000 times slower response time than computer chips, it (so far) beats the computer in complex tasks, such as image and sound recognition, motion control and so on.

Inspired by biological nervous system, neural network technology is being used to solve a wide variety of complex scientific and engineering problems.

Neural networks are ideally suited for such problems because, like their biological counterparts, a neural network can learn, and therefore can be trained to find solutions recognize patterns, classify data, and forecast events.

Unlike analytical approaches commonly used in fields such as statistical, neural networks require no explicit model and no limiting assumptions of normality or linearity. The behavior of a neural network is defined by the way its individual computing elements are connected and by the strength of those connections or weights. The weights are automatically adjusted by training the network according to a specified learning rule until it properly performs the desired task.

The neural network is a good method for textile data analysis because:

- Neural networks outperform current methods of analysis because they can successfully,
- Deal with the non-linearities of the textile industry we live in,
- Be developed from data without an initial system model,
- Handle noisy or irregular data from the real world,
- Quickly provide answers to complex issues,
- Be easily and quickly updated,
- Interpret information from tens or even hundreds of variables or parameters,
- Readily provide generalized solutions.

Backpropagation Method

Backpropagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by us. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities.

Standard backpropagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term backpropagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. There are a number of variations on the basic algorithm that are based on other standard optimization techniques, such as conjugate gradient and Newton methods. The neural network implements a number of these variations.

Properly trained backpropagation networks tend to give reasonable answers when presented with inputs that they have never seen. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs.

The primary objective is to use the backpropagation training functions to train feedforward neural networks to solve a textile specific problem. There are generally four steps in the training process:

- Assemble the training data,
- Create the network object,
- Train the network,
- Simulate the network response to new inputs.

Textile Approach

In this work, we use the backpropagation method to optimally determine the raw cotton blends characteristics for to produce combed yarn for knitting.

The database of our study contains the raw cotton characteristics and all the combed yarn properties that are produced by spinning mill.

We divide the study in four phases:

In the first phase, we have assembled the training data. The raw cotton characteristics such as, Micronaire Index (MI), Span Length 50 % (SL50), Span Length 2.5 % (SL2.5), Strength (ST) are the inputs (I) of the neural networks model, in this step of the study.

The outputs (O) are the twist multiplier (AlfaNe), the Count (Ne), the Uster Quality Level (UQL), Unevenness (CVUster), Hairiness (Hair), Thin places (Thin), Thick Places (Thick), Neps (Neps), Tenacity (Ten), and Elongation (Elon).

In the second phase we create the network object where we linked the Uster Statistics information with the historical data from the spinning mill. The results of the response of the neural networks are shown in the Table 1.

In the third phase we retrain the network and we have the outputs for the spinning process by reversal neural networks use (Table 2).

In the fourth phase we simulate the network response to new inputs (Table 3).

Results and Discussion

We linked the Uster Statistics information with the historical data from the spinning mill. The results of the response of the neural networks are shown in the Table 1. The Uster Quality Levels are in the range 21 - 30.

This range is associated with a quality level not according with the mill quality specifications. Therefore, we must specify a better quality level, 10 in our case.

To meet this target, we re-use the neural network model, changing the input variables that will be the most important quality parameters of the yarn, for values levels according to the desired quality level (10): Uster Quality Level (UQL), Unevenness (CVUster), Hairiness (Hair), Thin Places (Thin), Thick Places (Thick), Neps (Neps), Tenacity (Ten), and Elongation (Elon) (Table 2).

However, if we want to increase the quality, we must change some technological spinning parameters. Therefore, we are obliged to increase the twist level, considering the range 4.2- 4.5.

The outputs, Micronaire Index (MI), Span Length 50 % (SL50), Span Length 2.5 % (SL2.5) and Strength (ST) present the new predictions values for the raw cotton properties that we must consider to reach our goals.

Just now, we are working with a theoretical model, even if very closely with the spinning technological reality.

After this, we must validate our spinning model. We choose three different raw cotton blends that meet the predictions of the neural network model. According with the spinning specifications of the mill, are spinned three different levels of yarn count (50, 40 and Ne 30), each one with two different twist levels.

The properties of the produced yarns are measured and further compared with the Uster Statistics Database.

The Table 3 shows that according with the yarn characteristics, these yarns could be classified with an Uster Quality level under 10 %, unless 2 cases concerning two yarns with count Ne 50 and 40, which are classified at the level 11 and 13 %.

Conclusions

The volume of information available for decision-making is growing at an unprecedented rate. Models, algorithms, and tools offered by decision-making theory, operations research, mathematical programming, and other disciplines have met some of these growing needs for data processing. The expanding scope of decision-making problems calls for a new class of computational tools.

Data mining satisfies some of these needs by offering capabilities to process data of different types (e.g., qualitative and quantitative) and originating at different sources. None of the traditional approaches is able to cover such a wide spectrum of data diversity.

The discovery of patterns in spinning data can improve the performance of this industrial process, revealing what factors affect the outcome and the patterns relating the outcomes with the production factors. Such patterns increase our understanding of these processes and therefore our ability to predict and affect the outcome.

Neural networks can be used as a powerful data mining tool for optimizing problems in Cotton Combed Spinning Technology using the ability to enhance the past behavior of textile processes.

Using a data mining approach we can crosslink historical spinning databases with the Uster Statistics to predict and to optimize new cotton spinning blends.

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Table 1. Initial Response of the Neural Networks.

O	O	O	O	I	I	O	I	I	I	I	I	I	I
MI	**SL 50**	**SL 2.5**	**ST**	**AlfaNe**	**Ne**	**UQL**	**CV Uster**	**Hair**	**Thin**	**Thick**	**Neps**	**Ten**	**Elon**
4.1	15.5	31.8	21.3	4.10	50	29.6	12.9	3.5	2.2	25.3	57.6	24.1	5.3
4.1	15.1	31.7	21.6	4.12	50	27.8	12.8	3.5	2.2	24.6	56.2	25.6	5.4
4.0	14.9	31.7	24.0	4.11	50	29.2	12.9	3.4	2.2	25.0	57.1	25.5	5.4
4.2	14.7	31.6	24.6	4.05	40	30.2	13.2	4.2	2.8	33.4	75.0	20.6	5.2
3.9	14.6	31.5	24.0	4.10	40	26.3	13.2	4.1	2.6	29.8	70.1	18.9	5.4
3.8	14.5	31.4	23.0	4.11	40	24.8	13.0	3.9	2.5	30.1	70.1	19.2	5.6
3.5	14.4	31.4	25.6	4.01	30	21.8	11.8	4.2	1.2	17.4	36.4	19.2	5.5
3.6	14.3	31.2	25.6	3.90	30	22.5	11.8	4.5	1.1	17.1	36.6	19.1	5.7
3.7	14.0	31.2	25.8	3.81	30	23.6	12.0	4.6	1.1	17.8	36.9	18.9	5.7

Table 2. Output for the Spinning Process by Reversal Neural Networks Use.

O	O	O	O	I	I	I	I	I	I	I	I	I	I
MI	**SL 50**	**SL 2.5**	**ST**	**AlfaNe**	**Ne**	**UQL**	**CV Uster**	**Hair**	**Thin**	**Thick**	**Neps**	**Ten**	**Elon**
3.9	14.3	30.8	21.7	4.56	50	10.0	12.3	3.1	1.2	17.8	38.9	26.7	5.6
4.0	13.7	30.7	22.3	4.58	50	10.0	12.3	3.1	1.2	17.8	38.9	26.7	5.6
3.9	14.5	30.9	22.2	4.57	50	10.0	12.3	3.1	1.2	17.8	38.9	26.7	5.6
4.4	13.4	30.5	21.8	4.50	40	10.0	12.4	3.8	1.6	16.6	51.9	23.3	5.5
4.5	13.3	29.8	21.5	4.56	40	10.0	12.4	3.8	1.6	16.6	51.9	23.3	5.5
4.6	13.4	29.3	22.1	4.57	40	10.0	12.4	3.8	1.6	16.6	51.9	23.3	5.5
4.6	13.1	29.4	21.6	4.46	30	10.0	11.4	4.3	1.0	11.4	28.7	22.2	5.6
4.5	13.2	29.4	22.3	4.33	30	10.0	11.4	4.3	1.0	11.4	28.7	22.2	5.6
4.7	12.9	29.1	22.0	4.23	30	10.0	11.4	4.3	1.0	11.4	28.7	22.2	5.6

Table 3. Validation of the Spinning Process Model.

MI	SL 50	SL 2.5	ST	AlfaNe	Ne	UQL	CV Uster	Hair	Thin	Thick	Neps	Ten	Elon
3.9	14.3	30.8	21.7	4.50	50	9.0	12.2	3.1	1.1	17.4	38.5	26.8	5.5
3.9	14.3	30.8	21.7	3.80	50	13.0	12.4	3.3	1.2	18.7	41.5	26.3	5.4
4.4	13.4	30.5	21.8	4.50	40	10.0	12.3	3.6	1.6	16.2	51.2	23.5	5.5
4.4	13.4	30.5	21.8	3.80	40	11.0	12.5	4.0	1.7	17.5	53.1	23.1	5.3
4.5	13.2	29.4	22.3	4.20	30	8.0	11.3	4.3	0.9	10.5	27.5	22.5	5.7
4.5	13.2	29.4	22.3	3.60	30	9.0	11.4	4.2	1.0	10.9	28.3	22.3	5.6