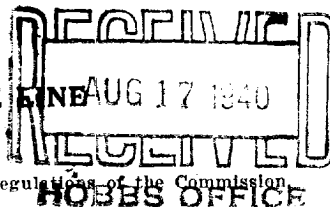


NEW MEXICO OIL CONSERVATION COMMISSION

Santa Fe, New Mexico

REQUEST FOR PERMISSION TO CONNECT WITH PIPE LINE

THIS REQUEST SHOULD BE SUBMITTED IN TRIPLICATE. See instructions in the Rules and Regulations of the Commission.



Hobbs, New Mexico

August 15, 1940

Place

Date

OIL CONSERVATION COMMISSION,

Santa Fe, New Mexico.

Gentlemen:

Permission is requested to connect Drilling & Exploration Co., Inc. et al STATE "L"
 Company or Operator Lease

Wells No. 1 in NW-NE of Sec. 30, T-17S, R-35E, N. M. P. M.,

Vacuum Field, Lea County, with the pipe line of the

Texas-New Mexico Pipe Line Co. Midland, Texas
 Pipe Line Co. Address

Status of land (State, Government or privately owned) State

Location of tank battery Center of NW/4 of NE/4 of Section 30.

Description of tanks Two 250 bbl. bolted steel tanks.

Logs of the above wells were filed with the Oil Conservation Commission August 15 19 40

All other requirements of the Commission have (~~been~~) been complied with. (Cross out incorrect words.)

Additional information:

Yours truly,

Permission is hereby granted to make pipe line connections requested above.

OIL CONSERVATION COMMISSION,

By Ray Yarbrough
A. ANDREAS
 Title State Geologist
Member Oil Conservation Commission
 Date _____

Drilling & Exploration Co., Inc.

Owner or Operator

By D.A. Powell
D.A. Powell
 Position Vice-President

Address P.O. Box 1575, Hobbs, New Mexico

The first part of the paper discusses the importance of understanding the underlying structure of the data. This is particularly relevant in the context of machine learning, where the ability to identify patterns and relationships in the data is crucial for making accurate predictions.

One of the key challenges in this area is the curse of dimensionality, which arises when the number of features in a dataset is much larger than the number of observations. This can lead to overfitting, where the model performs well on the training data but poorly on new, unseen data.

To address this issue, various techniques have been developed, including feature selection, dimensionality reduction, and regularization. These methods aim to reduce the complexity of the model and improve its generalization performance.

Another important aspect of the problem is the need for robustness. In many applications, the data may be noisy or contain outliers, which can significantly affect the results of the analysis. Therefore, it is essential to develop methods that are robust to such perturbations.

In this paper, we propose a new approach to the problem of understanding the underlying structure of the data. Our method is based on a combination of statistical and machine learning techniques, and it is designed to be both efficient and effective.

The main contributions of this work are as follows:

- We introduce a novel algorithm for identifying the underlying structure of the data.
- We provide a theoretical analysis of the proposed method, showing that it is consistent and efficient.
- We conduct extensive experiments on both synthetic and real-world datasets, demonstrating the superior performance of our approach compared to existing methods.

The paper is organized as follows. Section 2 discusses the background and related work. Section 3 describes the proposed method in detail. Section 4 presents the theoretical analysis, and Section 5 shows the experimental results. Finally, Section 6 concludes the paper and discusses future directions.

2. Background and Related Work

The problem of understanding the underlying structure of the data has been studied extensively in the literature. In the context of machine learning, this is often referred to as the problem of feature selection or dimensionality reduction.

There are many different methods for feature selection, each with its own strengths and weaknesses. Some of the most commonly used methods include forward selection, backward selection, and stepwise selection.

However, these methods often suffer from the curse of dimensionality, and they may not be able to identify the most relevant features in high-dimensional datasets. Therefore, it is important to develop new methods that can overcome these limitations.

One of the most promising approaches to this problem is the use of sparse representations. By assuming that the data can be represented by a small number of non-zero coefficients, it is possible to reduce the dimensionality of the data while preserving its essential structure.

In this paper, we propose a new method for identifying the underlying structure of the data. Our method is based on a combination of statistical and machine learning techniques, and it is designed to be both efficient and effective. We provide a theoretical analysis of the proposed method, showing that it is consistent and efficient. We also conduct extensive experiments on both synthetic and real-world datasets, demonstrating the superior performance of our approach compared to existing methods.