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A Deep Learning Model for Average Fuel Usage in Large Vehicles

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ABSTRACT

When it comes to creating unique machine learning models for fuel consumption, this research recommends adopting a data summary strategy based on distance as opposed to the conventional time period. This method is used with seven variables obtained from vehicle speed and road grade to create a highly predictive neural network model for typical fuel usage in heavy vehicles. The proposed approach can be readily designed and implemented for each vehicle in a fleet to maximise fuel efficiency. All of the model's predictors are averaged across predetermined time intervals. For routes that incorporate both city and highway duty cycle segments, a 1 km window is able to estimate fuel consumption with a 0.91 coefficient of determination and mean absolute peak-to-peak percent error less than 4%.

Keywords: Vehicle modeling, neural networks, average fuel consumption, KNN, data summarization, fleet management, statistical models, FNN

1. INTRODUCTION

Manufacturers, regulators, and customers are all interested in fuel economy models. They are required during the whole car ownership experience. In this study, we focus on predicting typical fuel use during maintenance and operation for heavy trucks. In general, there are three types of methods used for creating models of fuel consumption: • Models that are grounded in the physical sciences and built from a thorough comprehension of the system's dynamics. These models employ elaborate mathematical equations to describe the motion of the vehicle's parts at each time step [1, 2]. Machine learning models [3, 4], which are data-driven and reflect an abstract mapping from an input space consisting of a specified collection of predictors to an output space representing the goal outcome, in this case average fuel consumption. • Statistical models, which are similarly data-driven and create a relationship between a collection of predictors and a result of interest [5], [6].

The Cost and accuracy, relative to the needs of intended application, are two primary areas where the methods diverge.

Here, we offer a simple model that may be applied to any fleet of heavy trucks. A fleet manager's ability to optimise route planning for all vehicles based on each vehicle's estimated fuel consumption is greatly aided by having accurate models of all cars in the fleet at his disposal. Goods transportation [7], public transportation [3], construction [8] and garbage collection [9] all use fleets of vehicles. In order to be useful for any fleet, the technique must be generalizable to a wide range of vehicle technologies (current and future) and configurations without requiring in-depth familiarity with each vehicle's unique physical attributes and measurable parameters. After weighing the benefits of more precision against the costs associated with creating and tailoring a model for each vehicle in the fleet, machine learning emerges as the method of choice.

Existing work

Existing model that can be easily developed for individual heavy trucks in a big fleet is proposed for

If a fleet manager has reliable models of all the cars in the fleet, he or she may optimise route planning for the entire fleet based on the expected fuel consumption of each individual vehicle, guaranteeing that the route assignments are optimised to reduce fuel consumption across the board.

This method is used with seven variables obtained from vehicle speed and road grade to create a highly predictive neural network model for typical fuel usage in heavy vehicles.

For routes that incorporate both city and highway duty cycle segments, a 1 km window is able to estimate fuel consumption with a 0.91 coefficient of determination and mean absolute peak-to-peak percent error less than 4%.

Present work

As was previously noted, digital models of complex systems are frequently developed using artificial neural networks (ANN).Some of the challenges that machine learning models encounter when the input and output are in separate domains are brought to light by the models suggested in [15].The input in this study is the total distance travelled during the course of the study period, while the output is the total amount of fuel used.Where F() is the system, p are the predictors of input, and o are the response or output, the transfer function F(p) = o depicts the complex system.

In this study, we employ a specific type of ANN called a Feed Forward Neural Network (FNN).

Particle swarm optimization [20] and back propagation are just two of the many possible methods that can be used during training, which is an iterative process. It is planned that future research will investigate other methods in an effort to assess their potential to enhance the model's forecast accuracy.

For each training iteration, the network's weights are updated based on a random pair of (input, output) characteristics from Ftr. In order to do this, one must determine how far off the model's prediction from the actual output value is.

2.SYSTEM ARCHITECTURE

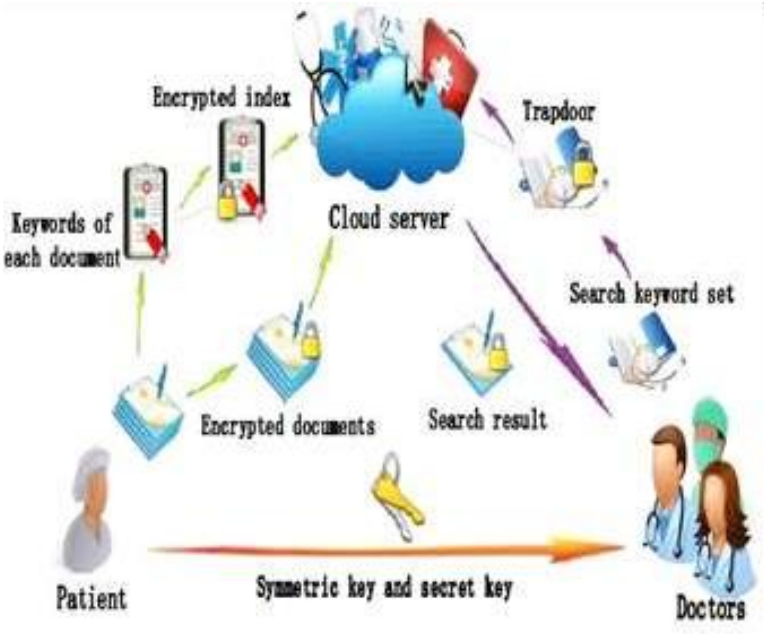

Fig. 2.1. System architecture

3. SYSTEM IMPLEMENTATION

The following modules are used to implement the system

- Trusted authority
- Patient
- Cloud server
- Doctor

4. TRUSTED AUTHORITY

As are third parties you may rely on. Use attribute-based encryption to protect the medical records (ABE). Patients' medical records will be encrypted to prevent unauthorized access.

A patient uploads their medical records to a cloud server for the convenience and security of the corresponding search doctors. Data privacy is protected by encrypting all original documents using an attribute-based encryption strategy. Additionally, she creates a keyword for each outsourced content in order to improve the search engine's performance. The secret key of the secure KNN scheme is used to match the keywords to the index. Uploading the encrypted documents and indexes, as well as providing a secret key, takes place at this point.

5. MACHINE LEARNING

Before diving into specific methodologies, understand machine learning. Machine learning is sometimes categorized as a subset of AI, however this is deceiving. To understand machine learning, think of it as a way to construct models from datasets.

Machine learning involves building mathematical models to understand data. To consider a computer "learning" from data, models must have changeable parameters that may be altered based on observed data. Fitted to existing data, these models can anticipate and understand new data. I'll let the reader decide if mathematical, model-based "learning" is like human brain "learning." We'll start by categorizing the machine learning methods we'll investigate.

Categories of Machine Learning

The two most basic types of machine learning are supervised learning and unsupervised learning.

Using supervised learning, which involves modelling the link between data features that can be evaluated and a label that is linked to the data, it is possible to label data that did not have a label before. In classification, the labels are discrete categories, but in regression, they are continuous values. This is further broken down into the tasks below: In the next section, we'll look at both types of supervised learning in the real world.

As the phrase "letting the dataset speak for itself" suggests, unsupervised learning is the process of making models from the features of a dataset without using any labels. In these models, there are tasks like clustering and reducing the number of dimensions. Dimensionality reduction methods try to represent the data in a simpler way, while clustering algorithms try to find clear groups of data.

We have to use machine learning.

Humans are the smartest and most advanced species on Earth right now. They can reason, evaluate, and find solutions to even the most complicated problems. The best reason for doing this is "to make decisions based on data in a way that is efficient and can be scaled up."

In recent years, companies have put a lot of money into new technologies like AI, ML, and DL in order to get the most useful information from large amounts of data and solve real-world problems. These decisions made by computers can be called "data-driven decisions," especially when the process is being done automatically. Problems that can't be coded from the start can be solved by using data-driven decisions instead of programming logic. We can't live without smart people, but we also need to solve problems in the real world quickly and on a large scale. Because of this, machine learning is important.

Robotics and artificial intelligence (AI)

Machine learning models need time to do things like collect data, extract features, and find features.

Since ML technology is still young, it's hard to find experts in the field.

As ML keeps getting better, it faces the problem that it doesn't have a clear purpose and goal when it comes to making business problems.

If a model is too big or too small, it can't show a real-life situation as well as it could.

ML models have to deal with the curse of dimensionality because there are just too many features in the data. So, this isn't something that happens very often.

The ML model is hard to use in the real world because it is so complicated.

6. MACHINE LEARNING TECHNIQUES TO CONTROL THE HEAVY VEHICLES

Intelligent Transportation Systems (ITS) and computational systems' rapid development opened new scientific research in smart traffic safety with comfort and efficient solutions. Artificial Intelligence (AI) has been widely used to optimize traditional data-driven approaches in different research areas [1]. AI-based on the Vehicle-to-Everything (V2X) system obtains information from various sources, i.e., car, train, bus, etc., and enables to increase the realization of drivers and forecast to avoid accidents. This progression has directed to the opportunity to understand smart driving, which was built on the idea of copying real driving comportment, while avoiding human mistakes and bringing comfortable safety to drivers. Many services have been invented from crowd and light road traffic to adapting traffic, a legacy from self-based vehicle systems to the IoV [2]. IoV is addressed to change the interaction between the vehicles, roadside stations, on-board stations, and environments to communicate data and multimedia between various networks. The motivation of IoV is to be adopted and build the human-vehicle-roadside onboard IoT Connected services within the various vehicle and different networks.

Machine Learning (ML) is responsible for a wide range of AI applications. The ML techniques are unsupervised, supervised, and reinforcement learning. In the unsupervised ML scheme, training depends on untagged data. It tries to find an adequate representation of untagged data. While, in supervised learning, it learns from a group of labeled data. In supervised learning, regression and classification schemes train the discrete and continuous data for prediction and decision-making. Reinforcement learning (RL) studies from the learning agent's activities from the consistent reward to capitalize on the notion of cumulative rewards. The Markov Decision Process (MDP) is a sample of RL [2]. This scheme is a perfect technique for taking many issues' research problems in vehicular networks, such as in collaborative optimization of oil consumption for a specific area and optimum path forecasting of electric vehicles and minimizing traffic congestions.

7. CONCLUSION

Construct a machine learning model for each of the fleet's heavies in a short amount of time.

The seven predictors included in the model are as follows: the number of stops, the duration of each halt, the average speed, the characteristic acceleration, the aerodynamic speed squared, the change in kinetic energy, and the change in potential energy.

In this study, we introduce the final two predictors to better represent the typical dynamic behaviour of the vehicle. The model's predictors are all computed using data collected on vehicle velocity and road gradient.

Such data is easily accessible via the telematics devices increasingly found in modern automobiles. Not only that, but the predictors may be quickly calculated on-board based on these first two variables.

Plans for the Future

Average fuel consumption for heavy vehicles is predicted using Machine Learning Algorithms like ANN, which are described in this study (Artificial Neural Networks). The author has derived 7 variables from a dataset of heavy vehicles to forecast fuel usage.

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