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School of Computing

**Honours Project**

**Report**

***Using an Artificial Intelligence to predict used car sales and provide prediction insight***

**Scott Grant**

This report is submitted as part of the requirements for the degree of

**BSc (Hons) in Computing Science**

at Robert Gordon University, Aberdeen, Scotland

**I confirm that the work contained in this Honours project report has been composed solely by myself and has not been accepted in any previous application for a degree. All sources of information have been specifically acknowledged and all verbatim extracts are distinguished by quotation marks**

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# Abstract

# Chapter 1. Introduction

The project’s main objective was to create a tool using both Deep Metric Learning (DML) and k-Nearest Neighbour (kNN) to predict used car prices from a dataset. The secondary objective was to determine how well this would perform against comparison algorithms such as a baseline kNN trained on the base dataset, and Random Forrest (RF).

### Project Overview

### Aims and Objectives

### Statement

This honours project report was produced by Scott Grant in partial requirements for the BSc (Hons) Computing Science at Robert Gordon University

### Sign posting paragraph

Chapter 2 contains the literature review

Short para stating which section contains what.

# Chapter 2. Project Scope

## 2.1 Literature Review

### 2.1.1 Used Car Valuation Review

Selling used cars is generally a hard metric to gauge as unlike with brand-new cars there is no Manufacture Suggested Retail Price (MSRP) to give the seller an idea of how much the item is worth. This means that private sellers need to balance many different factors which could affect the value, factors such as condition, age, accident history etc. This means there is no real metric to which a seller can easily price their car to.

The selling of used cars has also become increasingly complex in recent years, with prices fluctuating due to factors such as the COVID-19 Pandemic chip shortage (Sillars 2021) or the new Ultra-Low Emission Zone (ULEZ) (Simpson 2023). Historically, there were resources such as the Parkers monthly car valuation book (Adams 2022) or the Kelley Blue Book (KBB) (Kelley Blue Book 2023) in which they publish books which advise readers on what price to expect for used cars. The problem with paper published books is that the books are out of date the moment they are printed, and so cannot keep updated with rapid changing prices. KBB state on their website that the used car valuation they offer is not based on a formula or algorithm instead based on vast knowledge of the industry (Kelley Blue Book 2019). This method of pricing is vague, as with no insight to the actual valuation process it cannot be said that the KBB is an un-bias party, and so prices may be swayed.

In 2021, the UK was recovering from the economic impact of the COVID-19 pandemic lockdown, with the economy growing 7.6% that year (Clark 2023). This recovery helped lead to the number of used car sales exploding like never seen before. The Society of Motor Manufactures and Traders (SMMT) said that “April saw growth of 307.4%, followed by the best May and June since records began.”(SMMT 2021). This explosion in demand lead to prices soaring that year, with the average used car price increasing by 30% over the previous year (Muir 2023). This rise in used car sales and prices could not have been predicted, and so sellers would find gauging used car prices extremely difficult.

New measures being implemented by the UK government have also affected used car sales. The Ultra-Low Emissions Zone in London was rolled out to improve the air quality (Transport for London 2023b) with fines of £12.50 per day to Internal Combustion Engine (ICE) cars that don’t meet the set criteria. Most petrol cars manufactured after 2005 and diesel cars from 2015 are exempt (Transport for London 2023a). BBC News states that ULEZ compliant car prices have increased on AutoTrader by over 40%, they state that the median price beforehand was “£12,989” and afterwards was “£18,295” (Rufo 2023). Factors such as the ULEZ’s or rising fuel prices (Race 2023) could be reasons to why used Battery Electric Vehicles (BEV) sales are up by 81.8% as of Q2 2023 (SMMT 2023).

To make it easier for sellers to value their cars, there are many online free valuation tools available. Some of the most popular of these tools are RAC Cars Online Valuation (RAC Cars 2021), We Buy Any Car (We Buy Any Car 2023), AutoTrader UK (AutoTrader 2023) and Parkers UK (Parkers 2023). These tools work by collecting data about the vehicle such as the car brand, model, model variant, year, and condition, and then the details are processed through an undisclosed algorithm with a price estimation given back to the user.

The main problem with this process is that there is no transparency or justification in their pricing, as these tools are closed source. Many of these online tools offer to buy the car from the user at the end of the valuation process offering a quick process (See Figure 1.).

A screenshot of a computer

Description automatically generated

Figure 1 - Screenshot of WeBuyAnyCar's car valuation offer webpage

This means that these car valuation tools could be affected by alternative motives, such as valuing the car lower on purpose to increase resale profits. My problem would solve this problem by making a free and open-source car price prediction tool for anyone to value cars with. It would allow a fair and transparent estimation process as the goal is to create a highly accurate value estimation tool that also justifies the pricing, so the value is properly understood.

### 2.1.2 Car prediction papers

Due to car price prediction being a complex metric to gauge, there is much previous work done on car prediction models using machine learning. Most of these papers are using regression-based algorithms, such as Linear Regression, Lasso Regression and Random Forrest. Others are based off using the K-Nearest Neighbours algorithm, Neural Networks or Deep Learning.

In (Ashok Kumar and Samruddhi 2020) the K-Nearest Neighbours (kNN) algorithm is applied to a dataset obtained named “The Used Cars dataset” with the goal of analysing used car prices. To compare their results, a Linear Regression algorithm was used as a benchmark. kNN ended up achieving an 85% accuracy, 14% higher than the benchmark set by linear regression.

The conclusion on further work is brief in its suggestions for accuracy improvement however it is stated that “advanced machine learning techniques” would be applied and validating the model with different methods. This however is very vague and would benefit from more specific future goals such as defining what machine learning techniques could be applied to this problem. Techniques such as Deep Metric Learners would be an ideal to use for future as to my knowledge this has not been applied to price prediction before.

The referencing is also poor, with claims such as “Most of the people prefer to buy the used cars because of the affordable price” without any sources. This would infer that the paper is a less reliable source. However, this fact could have been confirmed by a source such as (Armstrong 2022). Here from the Statista Global Consumer Survey about US Consumers when purchasing cars, a low-price rank third overall, only beaten by safety and fuel efficiency.

In (Ganesh and Venkatasubbu 2019) multiple machine learning algorithms are applied to a 2005 dataset made by the Kelly Blue Book that has 805 entries. The goal of the research was to prove the hypothesis of “Multiple and Lasso Regressions are better at

predicting price than the Regression Tree.” by applying these three different supervised learning techniques on predicting used car retail prices and comparing the accuracy of each. The hypothesis was found to be correct, with Mean Error Rates (MER) used to rate the accuracy. Multiple Regression was found to be the best with a MER of 3.48%, while Lasso Regression had a MER of 3.51% and Regression Trees with 3.78%. In the conclusion for future work, it is suggested that algorithms such as Random Forrest should be applied to this problem to improve accuracy, and that to select more data from more recent sources to increase reducibility.

There is no discussion on what data pre-processing was done before the experiment, which could lead to the results of this paper being less accurate and reliable (Maharana, Mondal and Nemade 2022).

In (Varshitha, Jahnavi and Lakshmi 2022) multiple algorithms are applied to a used car dataset from Kaggle. The goal of the paper was to create a model that can predict used car pricing, whilst ensuring that there is no bias to either the owner of the vehicle or buyer. The pre-processing of the dataset was well documented and improves the reproducibility of the experiment. 5 different models were used, Linear Regression, Ridge Regression, Lasso regression, Deep Neural Network and Random Forrest. Deep Neural Networks performed second best, with a Mean Absolute Error (MAE) of 0.766 and a Root Mean Error (RSE) of 0.842. Random Forrest gained the best accuracy rating, with a MAE of 0.746 and RSE of 0.917.

For future work, the paper mentions how the algorithms used to create the used car price prediction tool, could be adapted for use in selling other used goods such as electronics too. It also mentions that by training the model on parts of a larger dataset rather than one small one, it could increase accuracy furthermore.

The research paper (Enoch Li and Bradford Lin 2021) implements two deep learning algorithms and compares them to linear regression on used car price prediction. The goal of the research is to more accurately be able to predict the car prices over existing literature on the subject. The deep learning algorithms used are two Multilayer Perceptrons (MLP), one is a TurnKey solution from sklearn (MLP1) and the other is a customised version of TensorFLow’s Keras framework (MLP2). The dataset used is 16,000 used car data points scraped from the Kelly’s Blue Book website with a 90/10 train test split. Dropping features such as the car colour. As there is no industry standard for naming colours, there could be “Ice White” and “Artic White”. This however could have been standardised in data pre-processing instead of simplify removing the feature by banding similar colours together. By removing this, the model’s performance would be less accurate as it is widely accepted across the industry that the colour of a car can affect the value(We Buy Any Car 2022) (AA 2018).

In their findings, linear regression performed very poorly with a Mean Squared Log Error (MSLE) of 2.61, while both MLP’s performed much better with MLP1 scoring 0.16 and ML2 with 0.08. While these MLP’s outperformed the linear regression algorithm, they were beaten by (Patch 2018) implementation of Ridge Regression with a MSLE of 0.7 on the same dataset. The papers justification for this was Patch had done different dataset pre-processing, with the removal of outliers and the model was tested on a trimmed dataset. It was then speculated that the MLP1 and 2 would have performed better than Patch’s on the same processed dataset. Rather than speculating, it would have been more accurate to implement Patch’s solution into their own and test the results. Patch’s paper is available on GitHub and with all the code used, meaning it is open source and therefore straightforward to implement.

The paper (Enci Liu et al. 2022) uses 3 neural network-based algorithms Back Propagation Neural Network (BPNN), GRA-BPNN (GRA) and PSO-GRA-BPNN (PSO) to predict used car prices on data obtained from China’s largest online used car website. Extensive data pre-processing is used here, with a final dataset of size 10,620. The dataset includes a field for car location, which is a unique but important field as some locations are more desirable to buy from than others (Motorway 2022). By including this, the results of the paper are more likely to have a higher accuracy by taking this into account. PSO obtained the most accurate score of a MSE of 0.48, compared to Random Forrest’s 0.84 which gives a strong argument in the ability of Neural Networks to perform price prediction task better than more traditional algorithms. However, Random Forrest took just 21 seconds to complete the task with PSO taking over 4 times longer at 94 seconds. In the conclusion it’s mentioned that PSO while very accurate also was worse at price prediction for high market cars, meaning more features may need to be added to increase accuracy.

In (Chuyang Jin 2021) 5 regression-based machine learning models are applied to a UK based user car dataset numbering 100,000 entries scraped from websites. However, the paper focuses on specifically the Mercedes part of the dataset numbering 13,120. This way of training a model on just a specific make could help negate the issue raised by (Enci Liu et al. 2022) of high market cars being harder to predict. Sufficient data pre-processing took place, with excellent data visualisation to show the effect this had.

Agreeing with the results of (Enoch Li and Bradford Lin 2021), (Varshitha, Jahnavi and Lakshmi 2022) and (Ashok Kumar and Samruddhi 2020) Linear regression performed the poorest with a R-Squared value of 0.72. This would back up that used car valuation is a complex factor and is not a linear scaling problem.

Of the 5 algorithms, Random Forrest performed the best with a R-Squared value of 0.90 however in the conclusion it is said that this could be improved upon by using a larger dataset or implementing other algorithms such as Naïve Bayes.

The paper (Varshitha, Jahnavi and Lakshmi 2022) was written with the goal of reducing fraud when buying a used car by the implementation of a highly accurate model with no bias to either the owner or the buyer. The algorithms used are a supervised learning artificial neural network based Keras Regression (using 10 layers), Random Forest, Linear, Lasso and Ridge Regression. The dataset used isn’t named, instead just referenced as from Kaggle. This is an acceptable method of referencing, however failing to detail the name of the specific dataset used causes an issue as there is many used car datasets on Kaggle (Kaggle 2023). The paper is a less reliable source as any reproduction of the work is not possible and so the claims and accuracy claimed cannot be verified.

In the results, Random Forest beat the Neural Network’s accuracy with a MAE of 0.75 and R-Squared of 0.92 compared to the MAE of 0.77 and R-Squared of 0.842 (with MAE generally the closer to 0 the better, and with R-Squared generally the closer to 1 the better). However, there is no explanation to why Random Forest is better, and no future improvements suggested that could improve the Neural Network to better predict used car prices. It is suggested that the models could be linked to a live web scraper, intaking current data about used cars. This would be a very useful idea, as the model would consistently be as up to date with prices as possible and increasing the dataset size consistently which would also help to improve the model’s accuracy.

Above, the suggestions made by the papers for future improvements are usually suggesting certain algorithms or frameworks that could be more accurate than current ones. Or by using a larger dataset which could improve performance by allowing the algorithm more references for the price prediction. Some papers mention impartiality and not ensuring no bias however, none of these papers focus on making the reasoning of the used car price prediction open. By adding some insight to the decision process made by the algorithm, the buyers and sellers could understand the features that are impacting the price the most.

To add insights to algorithms such as Random Forest would be near impossible, it works by combining multiple decision trees together (IBM 2023). This means that understanding what features are affecting the price prediction extremely difficult.

The paper (Martin, Wijekoon and Wiratunga 2020) while not related to used car price prediction, proves that DML’s can be very accurate especially when in comparison to algorithms such as KNN. (Ashok Kumar and Samruddhi 2020) found by using kNN in used car prediction an accuracy of 85% was obtained. If DML’s could be used here to further improve this accuracy, which is important as this would help make the tool a more reliable source for price predictions.

### 2.1.3 Deep Metric Learning papers

In the paper (Martin, Wijekoon and Wiratunga 2020) three different Deep Metric Learner (DML) algorithms are used with the goal of finding which is the highest performing in similarity-based return. The algorithms are used across three Human Activity Recognition datasets all of which are based on different activities called SelfBACK, Multi-Model Exercise Data (MEx) and a Physical Activity Monitoring dataset (PAMAP2). KNN was used as a benchmark model in which to compare the three DML algorithms against. Across all datasets, KNN was significantly outperformed by the DML’s across all datasets. The highest difference being in the MEx dataset, KNN scored 68.56% accuracy whilst highest performing DML was Matching Network (MN) using MLP with 94.19% and using Convolutional neural network (CNN) with 95.49%.

The paper (Wang et al. Oct 2017) aims to use Angular Loss (AL) to improve DML’s ability. The DML’s are used across three image-based datasets: a bird species dataset (CUB-200-2011), Stanford Car dataset and an online product-based dataset. There were 7 algorithms used, but the main comparison ones were the AL and N-Pair & Angular Loss (NP&AL). NP&AL was used to show that Angular Loss can also be applied to other frameworks such as N-Pair.

In the discussion about the results, it’s said that AL across all three datasets had increased performance over the baseline, however by applying it to NP&Al the best performance can be achieved across all tested algorithms. For future work it is stated that ideas such as implementing a clustering-based framework could be an improvement to performance.

The paper is well written with mathematical formulas, tables, and figures to help explain the narrative to the reader.

### 2.1.4 Conclusion

According to my research, currently there are no Deep Metric Learner papers on price prediction, and certainly not any on used car price prediction so I feel this subject area is a gap in research. By using DMLs it has potential to outperform the most accurate algorithms in this research area, while also having the ability to share insights about the decision-making process not available by algorithms such as Random Forrest. To the best of my knowledge no car price prediction papers look at insights for the users about the algorithm, therefore this is also a gap in the research that my project aims to resolve.

## 2.2 Requirements

The requirements are for a regressor based problem, in which the requirement prioritisation technique MoSCoW (Agile n.d.) is used to sort requirements by must have, should have, could have and won’t have.

### 2.2.1 Functional Requirements

* Artificial Intelligence Implementation
  + Must be using a Deep Metric Learner based algorithm for price prediction
  + Must use a dataset of used car selling data
  + Must process car input data given and give a price prediction
  + Must be an open-source tool with version control
  + Should manage an accuracy above 80% to ensure tool useability
  + Should be compared against a different machine learning algorithm
  + Could obtain a higher accuracy than the comparison algorithm as this would increase tool viability
  + Could use Random Forrest for comparison as this has shown to be one of the highest performers from the literature review
  + Won’t have any buyer or seller bias implemented as this tool is made to be completely impartial
  + Won’t perform a price prediction for anything other than a private car
* The dataset:
  + Must be populated with used car sales
  + Must pre-process the data to maximise the potential accuracy of the tool
  + Should combine multiple datasets. This could help to remove any bias one source may have.
* The output
  + Must contain a price prediction from the given dataset
  + Must contain at least one performance measure
  + Should use Mean Average Error
  + Could use additional performance error methodologies
  + Could use figures to display the performance differences
* Web Application
  + Could be implemented into a web application
  + Could use the Driver Vehicle and Licencing Agency (DVLA) dataset api to return a price based on a registration number input

### 2.2.2 Non-Function Requirements

* Security
  + No sensitive information will be stored or transmitted
  + Car information such as registration plates are public knowledge
  + The datasets obtained are from public data repositories such as Kaggle
* Capacity
  + System Requirements
    - If made into a web application the project should support modern browsers such as Chromium Based Browsers, Firefox
    - Safari support could be available
    - Mobile phone and tablet browsers will not be supported
    - Must be able to run on a 2020 MacBook Air M1 as that will be the development machine
    - Could also run on a windows-based Intel i5 Desktop as this would be the backup development machine
* Maintainability and Manageability
  + The project will be open sourced throughout the development of the project
  + This means that maintainability will be easier as bug reports, or improvements can be suggested by peers
* Scalability
  + It is only expected for this project there will be no more than one person using the application at a single time as this is a proof of concept
* Useability
  + The web application should be simple and clear which would help to increase accessibility by reducing clutter
* Accuracy
  + The application should be as accurate as possible as this would increase the reliability of the tool

# Chapter 3. Design

## 3.1 Methodology

How I went about the work and development methods

Link to best practice methodologies either waterfall or agile

Think about which one I actually did

Experiment design was, what did you try to find out (goal) and how did you decide what machine algorithm you were gonna implement and what comparison would be

How am I evaulatiing these, and talk through what it means

The project was developed using an Agile methodology (Atlassian 2024), in which I

## 3.2 Data and Toolkits Is this an appropriate title?

### Dataset

The dataset used in this project is a collection of cleaned used car advert data collected through data scraping of UK used car markets (Aditya 2020). The collection is split into 13 CSV files, 9 car manufacturers and the other 4 on specific car models however these were not used as they are duplicates. Each CSV contains 9 features, 7 categorical: ‘model’, ‘year’, ‘transmission’, ‘mileage’, ‘fuelType’, ‘tax’, and ‘engineSize’ and 2 numerical: ‘price’ and ‘mpg’. Together all the sets have 99,187 cars.

### Siamese Network

A neural network is a type of supervised machine learning that works by combining multiple layers of nodes each with an associated weights to classify and cluster data (IBM 2024a). A Siamese neural network works by comparing two or more subnetworks which generate feature vectors for each input (Essam and Valdarrama 2021). The Siamese network used in this project uses Keras’s Siamese network documentation example (Essam and Valdarrama 2021), which has been adapted for use with this dataset instead. I’m unsure how to reference this, ask Kyle.

### Triplet Loss

The Siamese network implements triplet loss to learn the embeddings necessary to cluster the dataset. The loss function uses a Triplet which contains three samples the anchor, positive and negative to compute the embeddings. The anchor is the selected datapoint, a positive is a randomly selected similar datapoint and negative is a random dissimilar datapoint. The triplet loss function is defined in Equation 1 below. Ask Kyle how to reference this formula correctly here, and if it needs to be in the current format then do I need a table of formula too?

Equation 1 - Triplet Loss Formula

To create the Triplets a custom triplet generator method was created, where it will return 3 nested arrays, inside the triplet array. The triplet is created by iterating through the dataset selecting an anchor. The positive is randomly selected from where the ‘make’ and ‘price\_range’ are the same as anchor, while the negative is randomly selected where neither of those conditions apply.

### K-Nearest Neighbour

The KNN algorithm selected was from the Sklearn library and is called ‘KNeighborsClassifier’. KNN works by using a distance function to calculate a particular datapoint’s nearest k number of neighbouring datapoints. The neighbours are then analysed and the class label with the largest number of neighbours is then predicted to the datapoints label. If the k value is 1, then the label of the nearest neighbour is assigned to the datapoint (IBM 2024b; Srivastava 2018).

### Overall Model

The Siamese Network with Triplet Loss is trained on the generated triplets and saves embeddings. The dataset is then embedded, and the KNN model is then trained on this. This model is then what is used for price predictions. Siamese networks work well with classifying similar datapoints, as they base the predictions based upon similarity to other datapoints while KNN labels the data based on the closest neighbour.

These two points are why this these technologies were chosen for this project works well, as generally a car with similar features to another will be priced similarly.

### Model Evaluation

To provide prediction comparison, a baseline KNN and RF models were chosen. KNN was chosen as this will provide a comparison to how well the embedded dataset compares with the original. RF was chosen as in my literature review it was found to be the highest performing algorithm across multiple papers in used car price prediction. The RF model used was selected from the Sklearn ‘ensemble’ library and is called ‘RandomForrestClassifier’. These two models provide a baseline and a strong contender to compare the embedded KNN model against.

### Accuracy Evaluation

To evaluate the accuracy of the models, Mean Absolute Error (MAE) and Real Mean Squared Error (RSME) were used. These methods are used over a percentage of correct predictions as is it is more useful to examine how close each model is to the correct figure. The used car prices are set artificially by sellers, not by a MSRP and so identical cars can have differing prices.

### Reproducibility

This project was developed in a Juypter Notebook file on the online cloud service ‘Google Colab’ using the T4 GPU Runtime. To use the libraries required for this project the following commands must be run at the start of each runtime to upgrade the environment.

Links to the Google Collab file and the GitHub Page are available in Appendix A.

# Chapter 4. Implementation

## 4.1 Dataset Exploration and Pre-Processing

### Dataset Import

When the collection of datasets is imported, the 9 CSV files are combined into a single pandas dataframe, with a new column made for the car manufacturer. The dataframe is then explored, by checking distributions of columns such as fuelType, transmission and make.

Table 1 - Sample of the combined dataset

A screenshot of a graph

Description automatically generated

### Feature Distribution

Many features of the dataframe, were analysed and plotted to display any imbalances, find outlying data points, and look for mislabelled data.

A graph of fuel type

Description automatically generated

Figure 2 - Distribution of the Fuel Type Column

In Figure 2 there is a clear imbalance in the distribution of ‘fuelType’, however both the two largest ‘Petrol ‘and ‘Diesel’ are very balanced in comparison to one another. There is very little representation for ‘Other’ and ‘Electric’, numbering less than 300.

A graph with blue bars

Description automatically generated

Figure 3 - Distribution of the transmission column

Figure 3 shows that is a balanced feature with many data points for each type of transmission other than the outlying ‘Other’ type.

A graph of blue bars with white text

Description automatically generated

Figure 4 - Distribution of car make

Figure 4 shows the unbalanced distribution of the make of car, with the largest brand having almost triple the representation of the smallest. Even with this difference, there is still enough data points for each make to have a good representation.

A graph of a car price

Description automatically generated

Figure 5 - Scatterplot of Price against count

Figure 5 shows the price distribution throughout the dataset, with the highest numbers of occurrences under £20,000. The average prices are a mean of £16,805 and a median of £14,495 which shows that the price distribution is positively skewed.

### Removing Outliers

Cars without enough representation are seen as outliers as there is such a large disparity between them and the other types in that feature that it would hamper results. Cars that met the following conditions were dropped from the dataset:

* A ‘fuelType’ of ‘Electric’ or ‘Other’,
* An ‘engineSize’ that occurs fewer than 50 times.
* Transmission value of ‘Other’
* Priced either under £2,000 or over £60,000
* Over 100,000 miles
* Over 20 years old
* Models with less than 10 datapoints

In total 2184 cars were removed from the dataset.

### Conversion into a Categorical Problem

To change the task of price predication from a regression-based to categorical, a ‘price\_range’ was created to replace the ‘price’ field. Every price was rounded to the nearest £500, as this would reduce the number of price points to 120 possible labels, while trying to retain as close to the original price point as possible.

A graph with blue and black lines

Description automatically generated

Figure 6 - Distribution of the price range field

After conversion into the ‘price\_range’ field, figure 6 shows the new distribution. By removing the outlying price points, the overall distribution is now less positively skewed, and closer to a normal distribution. The averages remain similar with a mean average of £16,629 and a median of £14,500.

### Preparation for machine learning

The conversion of string features into numerical representations needed to be done for the machine learning models. This is done as machine learning models are designed to handle numerical data. Mapping Dictionaries were used to do this by relating each string value to a number. This method was applied to convert the ‘transmission’, ‘make’, ‘fuelType’ and ‘model’ fields.

The ‘year’ field while containing numerical data, is represented categorically. This was converted to an age column instead to better display the relationship of price to year. This then will more clearly display the car’s age as a range of 20 different categorical values. A mislabelled car ended up with a negative age, and so this was dropped from the dataset. Figure 2 shows a sample of the dataset after this processing.

Table 2 - Sample of the processed dataset

A screenshot of a graph

Description automatically generated

The final preparation for machine learning was to split the ‘price\_range’ from dataset and then split the sets again into a training and testing sets. This was done using a test size of 20% and a random state of 42 to keep the dataset split the same for each test run.

## 4.2 Creating the Deep Metric Learner

### Creating the Triplets

The ‘create\_triplet’ works by intaking the whole dataset split into x and y components. It then iterates through x, randomly a positive sample of the same ‘make’ and ‘price\_range’ as the anchor. A negative sample is then randomly picked from any datapoint with a different ‘make’ and ‘price\_range’. This function requires a lot of computation and so a progress counter was added, which will display the percentage of triplet’s generated so far. Figure 7 shows the code used for this.

A screenshot of a computer program

Description automatically generated

Figure 7 - The triplet generator method

Figure 8 Shows an example generated triplet, where the second to last element in the array is the make, and the price range is shown underneath.

A white background with black text

Description automatically generated

Figure 8 - Example Triplet

### Creating the Siamese Network with Triplet Loss

The Siamese network here is heavily based upon the Keras documentation’s example (Essam and Valdarrama 2021). The distance function works by calculating the distance between embeddings. It uses the squared Euclidean distance between the anchor embedding and the positive embedding, as well as the anchor embedding and the negative embedding. This distance function is then applied to the triplets, and the Siamese model from the example is then created, with the summary of the layers shown in Figure 9.

A screenshot of a computer

Description automatically generated

Figure 9 - Siamese Network Summary

The embedded triplets are then split with 80% in train and 20% the validation set. The model is then compiled using an Adam optimiser of 0.0001 and trained to 50 epochs as the loss is unstable after this.

## 4.3 Creating the prediction models

### Selecting the k value

To create effective kNN models, the k value must be optimised to increase model performance. To do this, a range of k values between 1 and 14 was tested on the base dataset to find the optimal solution.

A graph with a line going up

Description automatically generated

Figure 10 - MAE against differing values of K

As figure 10 shows, the model best performs by only selecting the single nearest neighbour, and so a k value of 1 was chosen for both kNN models.

### kNN models

There are two kNN models used, one trained and tested on the base data and the other is trained and tested on embedded versions of the data.

### Random Forrest model

The RF comparison model is trained and tested on the base data. It was tested to see how it performed on the embedded data, however it performed much worse than even the baseline kNN model.

# 5. Testing and Results

## 5.1 Testing Methodology

To test how well the DML works at classifying data and clustering it around a point, a kNN algorithm is applied to the embeddings and this is compared against a baseline kNN model and a comparison RF model. The DML’s embeddings are also visualised through the Principal Component Graphs (PCA) in Figure 11 which is a comparison of the base dataset, against the embedded.

## 5.2 Accuracy Evaluation Methodology

To test the different models, MAE and RSME were taken as the evaluation metrics. These metrics are used over an accuracy percentage of correct predictions as it is more useful to compare how much the models are likely to be out by, than how often they are right in used car price prediction. As this is a used car market, prices for two identical cars could vary making an accuracy metric useless. By using MAE and RSME, an acceptable margin can be made. For example, predictions could say “this car is £22,000 ±£1500” or instead of a single price state a price range to the user £21,500 – £23,500.

## 5.3 Results

### Embedding Results

In principle component analysis, the idea is to find the dimensions that are more indicative of you separate the data. In Figure 11, 3 principal components per graph were selected. The scales of these however do not match the features of the dataset, as these have been transformed. If the clustering is successful similar coloured data should be pushed together, while dissimilar data is pushed further apart. In figure 11, the price\_range was rounded to the nearest £10,000, to provide a clearer separation of data as smaller figures leave the graph unclear.

A comparison of color and scale

Description automatically generated with medium confidence

Base Dataset

Embedded Dataset

Figure 11 - PCA graph displaying the clustering of the dataset

Figure 11 shows that the base dataset, has no clear separation of colour, the data is not easily separable and there are bands of colour to it, all of which indicate that it is not clustered from standard. The embedded dataset has clustered the lower priced cars, with them strongly clustered together in the right of the chart. As the price range increases the colour separation becomes less consistent. The banding of colours throughout the data suggests that the embedding is not perfect and struggles with proper separation of the prices. Ideally it would have a gradual gradient shift of car prices. However, even so the clustering is visible better than the base dataset and does show a colour gradient.

### Model Results

Table 3 - Each model's accuracy on the Kaggle Used Car Dataset

|  |  |  |  |
| --- | --- | --- | --- |
| Model | MAE | RSME | MAE decrease compared with baseline |
| Baseline kNN | 4572 | 6714 | ---- |
| Embedded kNN | 2543 | 4240 | 44% |
| Random Forrest | 1282 | 2035 | 74% |

Table 3 compares the each of the model’s MAE and RSME values. The results show that by embedding the dataset a 44% reduction in the kNN model’s MAE was achieved, meaning that the embedding is a more optimised representation of the dataset. This however was beaten by RF, which had a 74% decrease in MAE compared to the baseline kNN model. The dataset has a high number of categorical fields and as RF is made from multiple decision trees, it is very competent at this data type. The embeddings may have not learnt the relationships between the categories and the outcomes properly. This could be down to factors such as the triplet generator not being specific enough when selecting a positive sample. Rather than selecting a random datapoint from the same model and price\_range, if it tries to ensure that every field is as close to the anchor’s as possible, a stronger representation of the dataset may be made.

A graph with different colored bars

Description automatically generated

Figure 12 - Car Makes against average MAE

Figure 12 displays the average MAE for each car make. The car makes with the lowest average MAE are ford and Vauxhall, both are some of the most frequent occurring as shown in Figure 3. However, Toyota, Skoda and Hyundai have lowest number of occurrences yet also share a low MAE. This would suggest that all car makes have enough occurrences for it not to have a large effect on MAE. The more prestigious car makes such as Mercedes, BMW and Audi share the largest average MAE. This would suggest that the dataset is missing data to represent the prestige and how that effects the price. This story is reflected in Figures 13 and 14. Figure 13 displays the Top 10 car models with the lowest MAE, all of which being more common less prestigious brands. The Top 10 cars with the highest MAE, are all sport or luxury cars from prestigious brands. So overall, prestigious brands perform the worst which could be down to the lack of representation as shown in Figure 6.

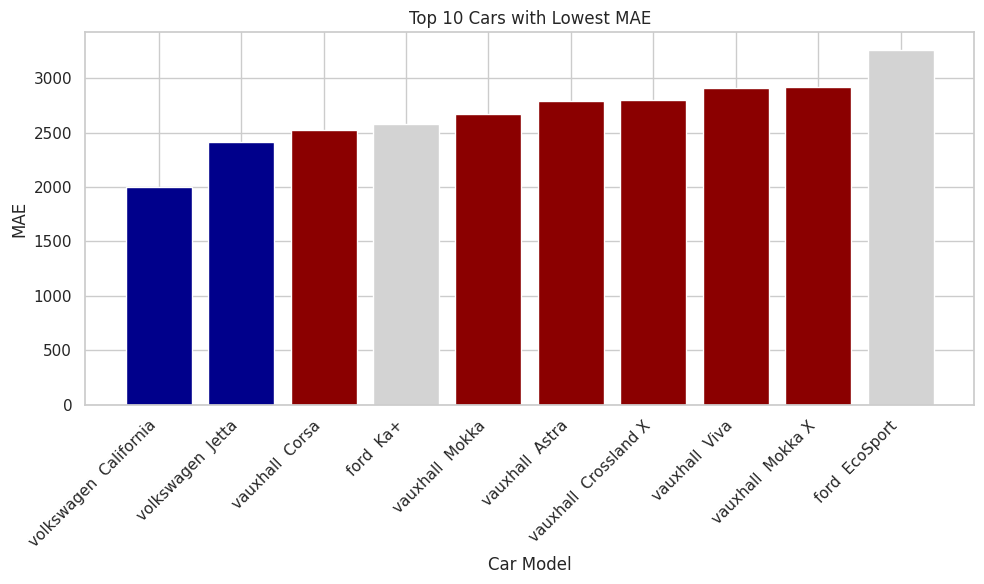


Figure 13 - Cars with the lowest MAE

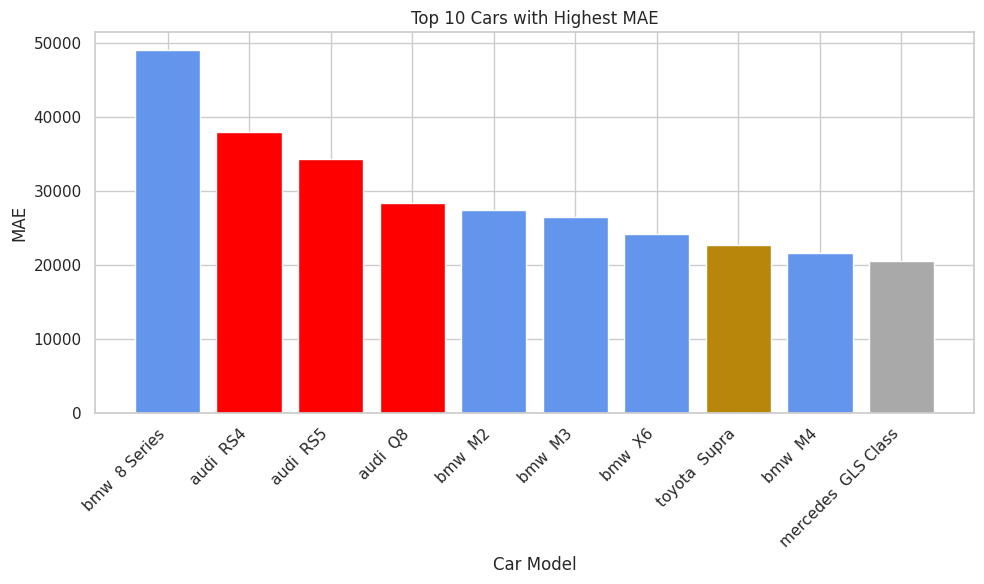


Figure 14 - Cars with the highest MAE

### Real World Example

An important note here is that the car market has substantially changed since the dataset was originally created back in 2020 therefore it isn’t the MAE on the data that is being measured, but the difference between each model’s MAE. 10 cars were taken off the used car online marketplace AutoTrader and entered a dataframe as shown in Table 4.

Table 4 - The real-world data collected

A table with numbers and text

Description automatically generated

The 3 models trained earlier were then tested on this real-world test set with the results shown in Table 5.

Table 5 - Each model's accuracy on the real-world example dataset

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | MAE | RSME | MAE decrease compared with baseline | MAE increase compared with Table 3 |
| Baseline kNN | 6000 | 6629 | ---- | 32% |
| Embedded kNN | 4667 | 5593 | 22% | 84% |
| Random Forrest | 3000 | 3431 | 50% | 134% |

The baseline kNN model has suffered the smallest percentage MAE increase, while both the embedded kNN and RF have much larger increases. These percentage increases are likely to be tied to how well a representation the model has on the Kaggle dataset. RF the best performing algorithm has the highest understanding of the base dataset, so when applied to the real-world set the MAE increases the most. The embedded kNN with have a better representation of the Kaggle dataset than the baseline kNN as all the embedding learnt by the Siamese network no longer hold true. This reinforces the idea that the embedding layers representation of the dataset is part of the reason why the embedded kNN falls short of RF.



Figure 15 - Example prediction of a user car

# 6. Evaluation

## Functional Requirements

Overall, 14/20 (70%) of the functional requirement objectives were met.

|  |  |  |
| --- | --- | --- |
| **Requirement** | **Was this met:** | **Comments:** |
| **Artificial Intelligence Implementation:** | | |
| Must be using a Deep Metric Learner based algorithm for price prediction | Yes | Implemented Keras’s Siamese Network with Triplet Loss. |
| Must use a dataset of used car selling data | Yes | Dataset is obtained from Kaggle and contains just under 100,000 records of UK Used Car Adverts data scraped. |
| Must process car input data given and give a price prediction | Yes | The real-world data section of the results shows this. |
| Must be an open-sourced tool with version control | Yes | Code has been stored on GitHub and Colab and is available in Appendix A. |
| Should manage an accuracy above 80% to ensure tool useability | No | **Refer to Chapter 5.2, i**t explains accuracy percentages are not used. |
| Should be compared against a different machine learning algorithm | Yes | The embedded kNN is compared against a baseline kNN model as well as a RF model. |
| Could obtain a higher accuracy than the comparison algorithm as this would increase tool viability | No | The embedded kNN outperforms the baseline kNN however RF is still the highest performing. |
| Could use Random Forrest for comparison as this has shown to be one of the highest performers from the literature review | Yes | RF was implemented as a comparison algorithm. |
| Won’t have any buyer or seller bias implemented as this tool is made to be completely impartial | No | No bias was intentionally implemented however by using a dataset of used car adverts this may negatively skew the price towards the seller. If records of actual car sale prices could be obtained, then this project could be made more impartial to both parties. |
| Won’t perform a price prediction for anything other than a private car | Yes | The dataset used only contains used car advert data. |
| **Dataset:** | | |
| Must populated with used car sales | Yes | - |
| Must pre-process the data to maximise the potential accuracy of the tool | Yes | Pre-processing was done and is detailed in the implementation. |
| Should combine multiple datasets. This could help to remove any bias that a single source may have. | No | There were no datasets combined in this project however, the project was applied to the Kaggle dataset, as well as the real-world example dataset. This is planned for future work. |
| **Output:** | | |
| Must contain a price predication from the given dataset | Yes | An example price prediction can be seen in Figure 15. |
| Must contain at least one performance measure | Yes | The performance measures used are MAE and RSME. |
| Should use MAE | Yes | - |
| Could use additional performance error methodologies | Yes | RSME was used. |
| Could use figures to display the performance differences | Yes | Figures 11-14 display this. |
| **Web Application:** | | |
| Could be implemented into a web application | No | The implementation of the tool into a website was out of the project’s scope, and so is under future work. |
| Could use the Driver Vehicle and Licencing Agency (DVLA) dataset API to return a price based on registration number input | No | There is no student licensing for the API, and so implementation would require financial backing. This is also under future work. |

## Gibbs reflective cycle analysis

Looking back on this project and its development I encountered multiple challenges throughout the project, specifically with the implementation of the Triplet Generator and Siamese Network. I struggled with the adaptation of Keras’s Siamese Network example as was applied to images, a completely different data structure to my dataset. Initially I felt overwhelmed by the project, I was dealing with technologies that I had no prior experience and knowledge about. Despite the struggles with the project, I succeeded in making progress and completing this section of the project through increasing my knowledge on the subject by consulting my supervisor and following the example. Looking back on it, this project identified multiple weak areas in my data science knowledge base. Overall, I feel that the implementation of Siamese Networks with Triplet loss has taught myself a great deal on the subject and I am much more confident in this subject area now. Going forwards, I am looking for a career in data science as I have thoroughly enjoyed this project.

# 7. Conclusion and Future work

## Legal, social, ethical, and professional issues

* Legally there should be no ramifications as this project only uses open-source libraries and is open sourced itself.
* Professionally if this project were to be made into a tool, there would be a responsibility to inform users on the model’s capabilities.
  + Accuracy metrics used to evaluate the model should be clearly stated
  + The data used to train the models should be open too. The models are trained from used car adverts, not the actual sale price and so this could lead to a seller bias.
* Both ethically and socially it is important that this project contributes towards good practice. By being open about the models used, and data trained on allows for peer review and scrutinization.

## Commercial Relevance

Unsure if this is going in right direction, ask Kyle

This project is aimed at the creation of a free, open-sourced, and bias free tool. If made into a web tool, this project would be a direct competitor to other car valuing websites. This would hopefully prompt the industry into disclosing more about the algorithms and data used to create these price predictions, or even open-sourcing the process entirely. At the least, this tool would serve as an impartial free online tool to compare the other car valuing tools against.

## Future Work

Overall, I feel the project has been a success, accomplishing the goal of creating an embedding layer to increase the performance of a kNN algorithm on Used Car Price Prediction. While not beating RF, the highest performing algorithm in this field according to my research, I still accomplished beating the baseline kNN by almost 50%.

For further development of this project, I would like to try to improve the DML’s classification accuracy further to try and match RF’s performance and eventually develop this into a web application. In future works, I would like to work on the triplet generator, as by developing a more complex method for sample comparison a better representation of the dataset could be made. This could be done by comparing every field in the dataset and trying to optimise a positive sample as like the anchor as possible. The dataset could also be further augmented to improve every model’s accuracy further. Brand and model prestige could be modelled by adding fields representing the brand prestige, and the MSRP. This would help the models distinguish the luxury and sports cars easier. If a dataset of actual car sales could be found, this would be ideal for reducing model bias. As the price would be representative of the price paid for the car, not the sellers asking price. Implementation of this tool into a web application was out of this projects scope however would be the final step in future work. If financial backing could be obtained the web application could implement the DVLA API to allow for users to enter their registration and get a price prediction back.

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# Appendices

## Appendix A – Project Links

Google Colab:

https://drive.google.com/file/d/1O-BxKoA9cwrcvEQ7CAcYGLvFJ0kmPKR9/view?usp=sharing

### UPDATE THIS LINK WITH UPDATED VERSION AFTER COLAB IS CLEANED UP!!!

GitHub: https://github.com/ScottGrant528/honours

## Appendix B: Project Log

### Source Code, Test Plans and other relevant documents