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Car Matching Algorithm CARM.A. Project Proposal

CSE6242 Fall 2019 | Team 8

Introduction

Due to rising new-car prices and a cultural shift amongst Millennials, used car demand is booming in the United States, outpacing new car sales over the last few years. In 2018, around 39.4 million used cars were bought in America compared to 17.3 million new cars (McKinsey). Buying a second-hand car can be a harrowing experience for the inexperienced. Majority of automobile sales websites (Autolist, 2019) rank car listings based on expert ratings (Kelley Blue Book Co., Inc., 2019) and sellers' advertising fee (Autotrader, 2018). These neglect reliability, safety ratings and model-specific design issues. We present Carma, a used car recommendation platform that improves inexperienced buyers' shopping experience by aggregating car reliability information from third-party websites to make car-buying decisions easier.

Figure 1. Sources used to shop for cars (Autotrader, 2018)

Problem definition

Two in three buyers in the used-car market are uninformed and have very little knowledge of cars (Autotrader, 2018). These buyers are highly reliant on branding and marketing of the car for their purchase decision. Buyers currently look for fragments of information across sites, which is inefficient and difficult. Figure 1 (above) shows that most used cars buyers mostly rely on third-party sites (Autotrader, 2018). Most expert reviews also neglect performance deterioration over time. Therefore uninformed buyers are unable to knowledgeably filter by brand, mileage and model (Autolist, 2019) and end up making suboptimal purchases.

Survey

Asymmetric information

Most studies into the used car market agreed that there is a large gap in information between buyers and sellers (Dangol, Jitpaiboon, & Walters, 2007) and is disadvantageous to buyers. Used car buyers are often subject to the "brand halo" bias (Sultan, 2010; Häubl, 2000), causing them to judge a brand's reliability by the average quality of its cars and ignore model-specific design flaws. Similarly, buyers are likely to mistaken more expensive cars to be of higher quality, when used car are priced independent of quality in reality (Lacetera, Pope, & Sydnor, 2012). Other than branding and marketing, buyers also overemphasized the car's mileage when examining how safety the used car option is (Vrkljan & Anaby, 2011).

Knowledge Bias

Experienced car buyers can overcome these biases by researching online. However, the majority of buyers are sensitive to the convenience of information (Bae & Benítez-Silva, 2011; Willmott & Warren, 1987) and were turned away by sparse information online. These information biases combined with abundant options available contributed to lower quality of decisions made by used car buyers (Darbrowski & Acton, 2010). By taking buyers' inputs (Callahan & Koenemann, 2000) and applying preference-based pre-filtering (Vila, 2011), Carma only displays a fraction of car listings to buyers. Using an interactive clustering map in lieu of a list of recommendations, users are more likely to be converted into buyers (Rohm, 2004; Rohm, 2004).

Success metric

So given a world with perfect transparent information, what are buyers looking for in a used car? Surveys showed that buyers value safety and reliability over design and performance (Prieto, Caemmerer, & Baltas, 2015). A successful used car purchase can be defined as: positive customer response post-purchase, no repair requirements pre-sale and little to no repair expenditures post-purchase (Shende, 2014). Different research indicates that reliability of second-hand cars may have little to do with their mileage (Betts & Taran, 2004), age (Consumer Reports, 2009). Instead, factors like engine power, reliability scores by rating agencies (Rijnsoever, Farla, & Dijst, 2009) and whether or not the model has an outstanding recall (Kim, 1985) indicate a reliable used car.

These studies suggested variables that buyers should and should not consider when making a used car purchase, however it is unclear how buyers should juggle all these factors. Carma aggregates all factors into a single quality metric, allowing users to research information, evaluate alternatives and schedule a test drive in one platform (Ginter, Young, & Dickson, 1987).

Solution & Innovations

Our solution is to create a one-stop platform that consolidates information from various sources and create a ranked list of recommended listings in the area, minimizing the effort for uninformed buyers to make a decision. We plan to overcome limitations of existing platforms through features such as:

1. Aggregate used car listings from multiple sources and incorporate additional dimensions (recalls, resale value, fuel economy, etc) to provide a holistic overview of a car's performance at the time of purchase and over time, rather than that of a new car fresh out of a factory.

2. Users can select attributes relevant to them through filters rather than screening cars based on technical specifications.

3. Visualizing ranked recommendations as interactive clusters instead of recommendation listing.

Data

Data	Source	Collection Method	Notes
Car Listings	Dealer websites, Craigslist	Scrapy, MarketCheck API	To maximize the range of car listings included in the platform from dealership to personal seller listings, we sourced live data using the Marketcheck API and used scrapy to scrape Cars & Trucks postings on Craigslist. Scraping Craigslist data involves complex cleaning and text processing, therefore the data is scheduled for daily updates. As the data is presented to the client by location, we will maintain at least 200 listings within 50 miles of any zip code, if it exists.
Reliability Data	National Highway Traffic Safety Administration(NHTSA)	NHTSA API	NHTSA requires all manufacturers to file a Defect and Noncompliance report and a quarterly recall status report in compliance with the Federal Regulation 49 Part 573 which identifies the requirements for safety recalls. We used NHTSA API to download the recall data. We assigned a severity index based on the type of recall,

			with 0-4 being minor or luxury parts, 5-7 being important components which may lead to accidents and 8-10 being the most severe and fatal components.
Ratings Data	JD Power, Kelly Blue Book (KBB)	Python, Beautiful Soup, Regex	Traditional car ratings from experts were drawn from the websites of JD Power and KBB. Both of these websites don't provide a public API, therefore, we implemented a scraper using BeautifulSoup and Regex operations. In JD Power website, overall car ratings, as well as reliability, driving experience and resale value ratings were extracted for each car model of every mainstream car makes for the past 20 years (5276 car models). We also scraped Expert ratings from KBB. However expert ratings are not available prior to 2011 (only 2243 are available out of the 5276 models). We also collected consumer ratings, fuel economy and textual analysis on the strengths of car models. We may use text-processing techniques to extract keywords from the descriptions and categorise cars into sub-genres such as family cars or road-trip family cars for tailored recommendations.

Approach: Ranking algorithm

Carma's value proposition is to create a *better* used car ranking based on reliability and curate car listing recommendations in a *more user-friendly* interface. In practice, whether or not Carma's ranking algorithm is in fact better and is more indicative of used cars' reliability can only be measured through customer safety and satisfaction (Shende, 2014) after completion of the tool. This brings difficulties to the design of the ranking algorithm, as we strive to create a different algorithm as opposed to what currently exists, yet our results cannot be validated.

Our solution is to craft a simple formula to weigh different variables that are known to impact used cars' desirability, based on academic journals and industry publications. This allows us to fine tune the formula at a later stage.

The following table illustrates our predicting variables and how they are used in our model:

	Metric	Source	Suggested importance	How is the metric incorporated in the model			
				Reliability	Driving	Resale	Fuel

					Experience	Value	Economy
1	Overall Rating	JDPower	Not mentioned	Disregard, only use in final product evaluation, to compare our output recommendations against.			
2	Quality and Reliability Rating		Important	Coefficient = 0.4			
3	Driving Experience Rating		Important		Coefficient = 0.5		
4	Resale Value Rating		Not mentioned			Scaled Score	
5	Expert Rating	KBB	Important		Coefficient = 0.5		
6	Consumer Rating		Below average	Coefficient = 0.2			
7	Combined Fuel Economy		Not mentioned				Scaled Score
8	Number and category of recalls	NHTSA	Average Importance	Calculate recall score, Coefficient = 0.4			
9	Listing's mileage	From individual listings	Important	Coefficient for reliability rating			

` Suggested importance according to academic journals and industry publications

Overall Ranking Function

$$Score = 0.25 * Reliability + 0.25 * DrivingExperience + 0.25 * ResaleValue + 0.25 * FuelEconomy$$

The overall ranking is initialized to be a weighted average across four key factors:

- Reliability: Whether the car will last without incurring significant repair expense?
- Driving Experience: How is the design, comfort, functionality, control and technology of the vehicle?
- Resale Value: How much will the car value depreciate over the next 2 years?
- Fuel Economy: What is the combined fuel economy of the vehicle?

The weighting of these factors will change based on user inputs. Using slider bars, users can weigh the relative importance of the factors.

All inputs will be scaled based on the range of values. For instance the Fuel Economy score will be calculated as:

$$ScaledFuelEconomyScore = \frac{MPG_{Listing} - MPG_{min}}{MPG_{max} - MPG_{min}}$$

Reliability

$$Reliability = 0.4 * mileageFactor(QualityReliability) + 0.4 * RecallRating + 0.2 * Consumer$$

- $mileageFactor = \alpha * (1 - \frac{CarMileage}{LifetimeMileageOfCarModel})$
  Value of α captures the inverse relationship between mileage and reliability.
- Quality Reliability: JD Power's Quality and Reliability Rating
- Consumer Rating: KBB Consumer rating considered less important in most research (Rijnsoever, Farla, & Dijst, 2009), therefore has a smaller coefficient
- Recall Rating: Maximum severity level across all recalls of the car model. This metric accounts for the likelihood a failure would harm the driver.

Other Factors

$$DrivingExperience = 0.5 * DrivingExperience + 0.5 * Expert$$

$$ResaleValue = ScaledResaleRating$$

$$FuelEconomy = ScaledFuelEconomyScore$$

Limitations

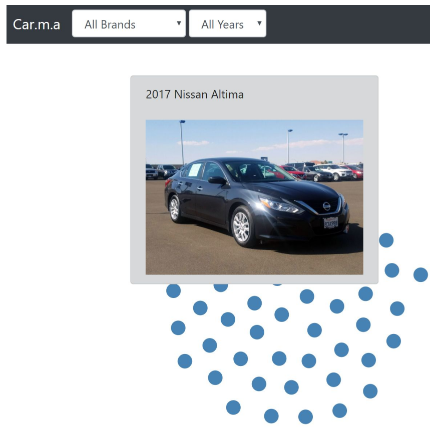
Due to the scope and timeframe, our project has a few limitations. First, the coefficients of the overall weighting function are informed by qualitative data, as there are no publicly available quantitative data comparing importance of car-buying considerations. Next, we do not have access to raw survey data. Taking aggregates as inputs is risky, as we have little understanding on distribution and statistical significance of the scores and fairness of the data collection method. Some car-rating platforms were suspected for charging car manufacturers marketing fees to skew the ratings. Our tool risks providing inaccurate recommendations due to low quality inputs.

Approach: Visualization and Infrastructure

System Architecture

The backend architecture is based upon a MEAN stack while the frontend interface is built with a combination of bootstrap and D3. The use of Express.js and Node.js allows the databasing load to be shouldered by the server instead of loading the entire dataset onto the client's browser and allows the application to scale to larger listing data. The combination of D3 and bootstrap lets us build a responsive and flexible web application that presents data dynamically.

User Interface



Sample User Interface

The user interface will consist of circles grouped together either by a user selected property, or micro-genres as previously defined. Examples of user selected properties include the year, make, and model. To clearly define the rank of each listing, the ranking will be inversely proportional to the size of the node, such that the most recommended listing will be the largest node. The color of the node will be determined by the price, while the details of the listing will be shown in a tooltip (not shown in sample).

Experiments/ Evaluation

To ensure the success of our platform, there are two key questions to be answered:

1. [User Experience] Does our application improve on users' current car-buying process?
2. [Effectiveness] Does our platform recommend reliable cars?

User Experience

To evaluate user experience, we will use a survey to gather users' feedback on the content and user interface of the tool. We will also monitor other metrics on the website to understand how users are using our platform.

Users will be shown a test application with no guidance or prompts. They will then be asked to select a listing that they would most likely purchase a car from. A feedback survey will then be conducted with the following questions.

Feature	Question
User Interface	How much guidance do you feel is required to select a car you like? Was it intuitive that the larger the node, the higher ranked the car is? Was it intuitive that the darker the node, the more expensive the car is?
Diversity of review sources	Do you feel that you need to visit other review websites after using our application

While they are using the application, the following metrics will be monitored:

Feature	Metric
User Interface	Number of filters used Most commonly used filter Most common sorting method
Diversity of review sources	Number of external websites visited
Ranking Algorithm	Number of listings opened

Effectiveness
As discussed, platform's effectiveness is hard to measure as most reliability metrics (Shende, 2014) are measured via long term post-purchase. We can conduct a post-purchase user satisfaction survey after the application deployment. The results of the survey can be used to fine tune the ranking algorithm.

Prior to post-launch survey, we can only conduct the initial experiment qualitatively. We will compare our rankings with other established car review websites which do not address all of the factors we considered and are not included in the dataset. Any discrepancy between the two rankings should be explainable.

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- Pre-release Comparison
  To test our ranking, we will compare it to other car review rankings that are not in our input dataset. The discrepancy should be explainable by comparing the following factors.

Factor	Possible Issues
Drivetrain	Are there any known design issues that causes the car to not start? Is there a part that requires a strict maintenance schedule (E.g. Timing belts must be changed at 60k miles)
Electronics	Are there any common electrical failures due to poor design? Is there any software updates mandated by the manufacturer due to a defect?
Safety	Are there any recalls that are hazardous to the driver? Are there instances where a design failure caused an accident or death?

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- Post-release user survey
  This feedback survey is designed based on the reliability metrics found in our literature review.

Metrics	Question
Repair Cost	How much did you spend on repairing the car right after you bought your car? How much did you spend on repairing the car 1 year after you bought your car?
Customer Satisfaction	Did you buy a car that was ranked in the top 3? Are you satisfied with your car? How many listings did you look at before purchasing your car?

Conclusions and discussion

[Work in progress]

Plan of Activities

Phase	Milestone	Initial Deadline	Updated Deadline	Member Responsibilities
I	Finalized project scope	10/06	10/6	• Aditi Goenka: created ppt slides • Ling Yiu Ku: cleaned & finalized report • Ngan Le: wrote proposal doc • Rishi Bubna: wrote proposal doc • Yong Jian Quek: presented in class • Zhe Min Chia: literature survey research *All: brainstormed, discussed and finalized project scope*
II	Scrape necessary data. Minimum Viable Product is able to aggregate listings from different sources with required metadata	10/20	11/08	• Aditi Goenka: scrape recall index from NHTSA • Ling Yiu Ku: scrape listing from Craigslist • Ngan Le: merge scraped data • Rishi Bubna: scrape rating from KBB • Yong Jian Quek: scrape listing from martketcheck • Zhe Min Chia: analyze scraped recall data to a single recall index score *All: derive ranking algorithm and experiments/ evaluation.*
III	Platform is able to filter car listings by user requirements *(Midterm check for success)*	11/03	11/10	• Aditi Goenka: search top car selection options preferred by users, write progress report • Ling Yiu Ku: research innovative website designs, write progress report • Ngan Le: research top car selection option preferred by users, write progress report • Rishi Bubna: research innovative website designs, write progress report • Yong Jian Quek: implement front/back end design of client website and server, write progress report • Zhe Min Chia: carry on part I of ranking algorithm implementation. Results will be included in the progress report. *All: discuss how user preference info can be incorporated in the ranking algorithm.*

IV	Devise ranking algorithm	11/24	11/24	• Aditi Goenka: implement variable selection • Ling Yiu Ku: train data to build ranking model • Ngan Le: handle missing values • Rishi Bubna: implement outlier removal • Yong Jian Quek: implement algorithm in the application • Zhe Min Chia: compare algorithm outputs with 1 competitor.
V	Test the weighting function and create an intuitive visualization *(Final check for success)*	12/01	12/01	• Aditi Goenka: gather results from cars.com for model validation • Ling Yiu Ku: design survey for real user feedback • Ngan Le: gather results from edmunds.com for model validation • Rishi Bubna: deploy created survey and gather real user feedback • Yong Jian Quek: implement visualization on the application • Zhe Min Chia: compare algorithm outputs with existing competitors.

All team members have contributed a similar amount of effort.

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