American Honda Motors Co – Improving Warranty Program Efficiency

Course Project

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Contents

Introduction & Problem Statement

The case selected for this project is the American Honda Motor Company's case from the SAS website[1]. The case revolves around effective management of Honda's warranty program. Before diving into the problem statement of the case, let's review what a warranty program is (more details on Honda's specific Warranty program in a later section).

Warranty program, in a nutshell, is a car manufacturer's guarantee of their quality of manufacturing and confidence that their product is of highest performance rating. As with any manufacturing process, there are control limits and some parts/assemblies are bound to fall outside of these limits and furthermore, flow through the process undetected. Warranty program provides a safety net for such occurrences where a part or system fails prematurely within a certain timeframe. This provides a mechanism to enhance customer satisfaction (CSAT). The way this typically works is:

1. A customer rolls into a dealership with an issue.
2. Customer Service representatives document the issue and check against the Warranty eligibility conditions of that vehicle.
3. If the issue qualifies for a warranty claim, the customer does not pay anything, and the issue is resolved at manufacturer's cost.
4. The service department then reviews the issue and decides whether a repair will resolve the problem, or the part would have to fully replaced.
5. If the determination is 'repair', the service department uses their mechanics to fix the issue.
6. If the determination is 'replace', the service department gets the parts from their on-hand inventory or orders a parts from Honda if not in stock at the dealership, and installs using their mechanics.
7. This warranty claim incurs different types of cost for Honda including hard costs like part cost, shipping cost, inventory holding cost, labor cost to repair or replace and cost of the loaner vehicle and soft costs like customer satisfaction degradation leading to lost sales and damage to brand image if certain issues become prevalent.

Given this overview, it will be easier to relate to the problem statement which has been broken out into two main sections:

1. How can Honda minimize the warranty costs including parts and labor? This problem includes following sub-topics each of which needs a solution.
    a. What is the optimum amount of spare parts inventory that should be kept at each dealership?
    b. How can the warranty service process at each dealership be optimized?
    c. Is the filed claim legitimate or Honda is paying a warranty claim that does not fall within the eligibility criteria?
    d. Is there a way to detect certain warranty issues early-on and proactively reach out to customers offering a lower cost service preventing a high cost fix later?

[1] https://www.sas.com/en_us/customers/american-honda.html

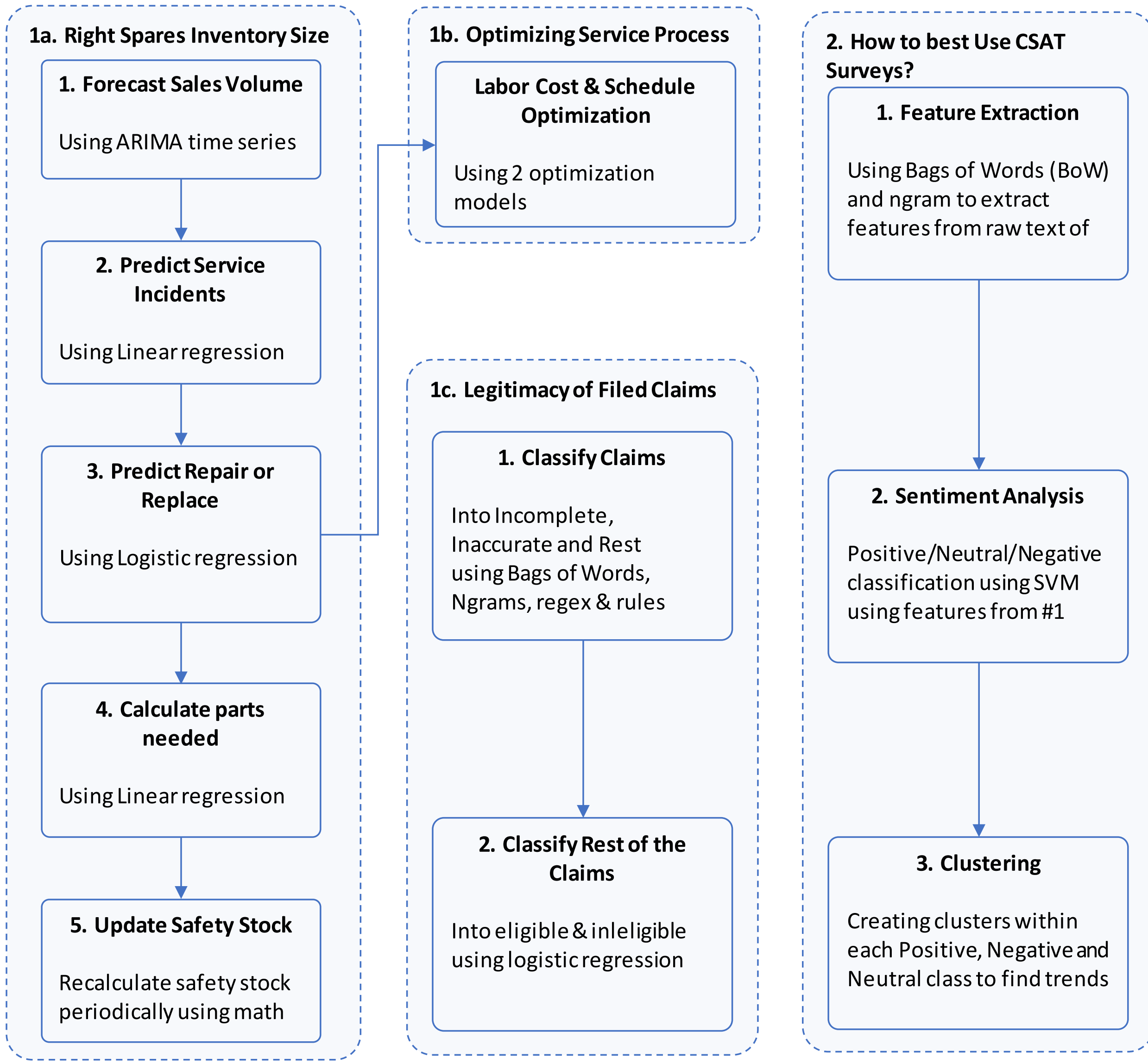
2. Customers fill out CSAT surveys at different points of the product lifecycle (purchase, servicing, sale). How can Honda use contents from this data to enhance customer experience, improve their product design and thus increasing brand loyalty?

Data in this case is generated at each dealership. When a customer comes in for a service, the vehicle is hooked to the Honda system and it captures different types of vehicle data (called Telematic data). Customer provides information about the incident during the visit, which is punched in by the representatives, which becomes another critical source of the data. Some vehicle models are fitted with telematic devices that can communicate data with Honda remotely as well. Public sources of data will also be used in the solutions proposed.

Each of these problems need their own evaluation and a solution. Some solutions are interconnected (as shown in the overall solution schematic in the next section). This is a very typical but very interesting problem that will require a multitude of analytics models to be applied in cohesion.

Let’s dive in!

Summary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Warranty Program Overview

In this section, an overview of Honda's typical warranty program is provided for context. Knowledge of these eligibility constraints will come in handy when we are evaluating solutions of different problems. Warranty eligibility of different models might vary slightly but Honda Civic[2] has been used to provide an example here.

Honda typically provides different types of warranties on a vehicle. For example,

- General warranty provisions & new vehicle limited warranty
  - 3 year or 36k miles coverage
- Powertrain limited warranty
  - 5year or 60k miles powertrain warranty
- Federal & California emissions warranties
  - This covers the systems in the vehicle that help control/measure emissions
- Hybrid powertrain warranty
  - Applies to all hybrid vehicles
- High Voltage Battery Capacity Warranty
  - Covers for greater than normal degradation of high volt batteries for 8 years / 100k miles.
- Tires
  - Original tires are covered by their manufacturer for greater than normal degradation and wear/tear.
- Seat belt limited warranty
  - Proper functionality of seat belts covered for 15 years or 150k miles
- Rust perforation limited warranty
  - 5 years (no mileage limit) rust coverage for any body panel

The other key thing to investigate in this section is ineligibility criteria for a warranty claim (this will come in handy for problem 1c). Following is a summary of these provisions:

- Failure of any part or accessory due to:
  - Abuse, misuse, accidental damage or acts of nature
  - Improper installation or maintenance
  - Low fluid level or use of fluids other than what's recommended by Honda
  - Installation of parts that's not recommended by Honda
  - Use of vehicle in competition or racing events
  - Improper fueling (e.g. diesel in gasoline engine vehicle)
- Installation of part or accessory that was not designed to fit that year or model of Honda.
- Vehicle with odometer that has been altered which impacts the ability to determine actual mileage.

[2] https://owners.honda.com/Documentum/Warranty/Handbooks/2020_Honda_Warranty_Basebook_Rev02_FINAL_-_SIS.pdf

- A vehicle that operates outside of the US, PR, US Virgin Island, Guam and the Commonwealth of Northern Mariana Islands.
- Failure caused by modifying or customization of the vehicle or by installing accessories not authorized by Honda.
- Any incidental expenses incurred due to the loss of use of vehicle.
- Any vehicle that has been declared a total loss or sold for salvage by the bank or insurer or has been issued a salvage title under the state's law. This doesn't apply to Emissions, Seat Belt and Replacement Parts Limited warranty.
- The time limit on the warranty starts on the date the vehicle is first put into use (first purchaser, leased etc.)
- Warranty does not cover:
    - Normal wear & tear of parts
    - Cleaning or polishing
    - Adding any fluids unless needed as part of warranty repair
    - Broken, chipped or scratches window glass
    - Expendable maintenance items like filters, brake pads.
    - Tires (warrantied by their manufacturer)
- Some items are covered for less time period
    - Key fob batteries – 6 months
    - Wiper blades – 6 months
    - Wheel balancing & alignment - 1 year or 12k miles
    - AC refrigerant – 2 years or 24k miles.

Problem 1 – Minimize Warranty Costs

As noted in the 'Introduction' section, there are two types of costs for Honda as part of the Warranty program, hard cost and soft cost. Problem 1 addresses the hard costs and provides solutions to minimize different components of this cost.

Hard costs include:

- Inventory holding cost (addressed in 1a)
- Labor cost to repair or replace (addressed in 1b)
- Cost of ineligible claims (addressed in 1c)

Problem 1a – What is the Right Level of Spares Inventory?

Inventory levels of spares inventory has a few types of costs associated with it. One is the carrying cost which typically runs 20-30% of the total value of inventory[3] and other is the intangible cost like opportunity cost of the money tied up in the inventory. Lastly, carrying insufficient inventory can have CSAT implications and additional costs like expedited shipping of the parts from factory warehouse.

Following is one of the many possible solutions to come up with right levels of spares inventory at a given dealership.

Step 1 – Forecast Sales Volume

In this step, we need to forecast the sales volume for each dealership. This will help predict the service incidents volume in the next step.

Data:

- Time series of historical vehicle sales data at a dealership level. The forecast will be predicted for each dealership.
    - This data could be available in Honda's central data warehouse (they must be capturing their sales information).
    - The data would include all new and used models and years sales out of a dealership.

Use:

- ARIMA timeseries model[4]
    - Auto ARIMA function in R could be used to recommend the right p, d and q parameters for the forecast.

To:

[3] https://www.investopedia.com/terms/c/carryingcostofinventory.asp
[4] https://towardsdatascience.com/an-end-to-end-project-on-time-series-analysis-and-forecasting-with-python-4835e6bf050b

- Predict a forecast of units of vehicles for a dealership
- The forecast's confidence interval would increase as we go further into the future meaning forecast would be more accurate for the near future.

Step 2 – Predict Service Incidents

The main question being addressed in this step is "given an amount of expected vehicles sales from a dealership, what would be the expected volume of service drive ins at the dealership's service department".

Data:

- Sales data for the dealership (historical and forecast from step 1). At least last one year plus future one-year forecast.
  - This would include attributes like VIN#, model, year, new/used, features, engine specs, information of the buyer like credit score.
  - This data would be available from Honda central data warehouse or might be kept at the dealership level.
- Service incidents data (historical)
  - This would include vehicles that came into the service department with issues excluding regular maintenance like oil change etc. This would include mileage information of the vehicle at the time they came in (response variable).
  - We would also capture number of service incidents per vehicle (another response variable for the 2nd model)
  - This data would be available from dealership's service department.
- Regular maintenance & telematic data
  - This would be the data from regular oil changes. An inspection is usually performed when a vehicle comes in for maintenance.
  - Newer models also have telematic data electronically captured by hooking car to the computer.
  - This data would include critical health information of vehicle systems and parts.
- Insurance information
  - This could include type insurance the vehicle owner carries, intended use of the vehicle (commercial or personal), expected yearly mileage etc.
  - Insurance data would be available from the financing institution of the vehicle. A lot of times, the dealership handles the financing (either directly or via partner bank) and should have this data available.
- Weibull probability
  - For $k<1$ for defective parts that would fail early, probability of failure at 30, 60, 90 and 180 days would be calculated using historical data.

Use:

- Linear regression

To:

- Predict the mileage at which the vehicle would come to the service department with any issue needing repair or part replacement.
    - Model will be trained & tested using historical sales and service data and the applied to the future sales forecast to predict the mileage at which cars would come into the service department.
- We would build a second regression model to predict the number incidents for each forecasted vehicle in operation.
- From this predicted mileage and predicted number of incidents, an estimated time series could be calculated to reflect number of vehicles that would come with repair needs.
    - E.g. if a vehicle is expected to be at 12k miles right now with expected incident to occur at 18k mileage and total of 2 predicted incidents. We could project that this vehicle would come in at 18k and then 24k mileage, probably twice in the next year assuming 1k miles per month.

Step 3 – Predict Repair or Replace

The goal of this step is to predict that among the group of vehicles predicted to come in with service needs (in step 2), which vehicle would need a repair, and which one would require a part replacement.

Data:

- For the population from step 2 that would come to the service department, same data as step 2 could be used in this step with the difference that our response variable will be binary 0/1 for service incidents that needed part replacement or not. 0 indicating repair only and 1 indicating part replacement.
    - This data would also be available from the dealership's service department.

Use:

- Logistic regression

To:

- Predict whether a vehicle would need a repair only or a replacement part as well.
- This would give us the population of vehicles coming into the service department that would need repair only and part replacement.
- The time series from step 2 could be updated to reflect the number of incoming vehicles to service department that would need repair and part replacement.

Step 4 – Calculate Parts Needed

In this step, using the population of vehicles that would need a part replacement we would predict the levels of inventory we would need in the future.

Data:

- Vehicles needing part replacement from step 3.
- Bill of Material (BOM) information for each model. This data would be available from Honda.

- Proportion of the BOM that is kept as spares inventory at the dealership. There would be obvious parts that would not be kept in inventory at all and are always ordered if needed. This would limit the population of parts to predict. Some parts would be shared b/w models as well. This data would be available from the dealership.
- We would build a dataset with following attributes:
    - A list by parts (only the portion that is kept in inventory)
    - Total quantity each part needed by models for the last one year (response variable)
    - Number of service incidents needing part replacement for each model for the last one year. If a part is on the BOM for a Model, we would put the total number of incidents for that part in the matrix. This is because our prediction is only whether a vehicle will need a replacement or not. We have not predicted at the level of which part would be needed. We will let the model learn from total incidents in relation to total part quantities consumed and make a prediction on part quantities needed.
    - Part price
    - Part lead time in calendar days
    - Part stock outs during last one year
    - Part safety stock level
- Example of this dataset:

Part Number	Price	Lead Time	Safety Stock	Model 1	Model 2	Model 3	Model 4	Model 5	Total Qty
A123	$250	10	100	10		50		30	277
B456	$300	15	100		50		70		400
C789	$350	20	50	10			70		392
D159	$400	10	50			50			329
E368	$1,000	5	25						355
F236	$1,500	30	25		50			30	182

Use:

- Linear regression

To:

- Predict the quantity of parts needed.
- The time period of prediction would be adjusted based on the number of incidents. For example, if only quarter's worth of incidents is entered in (from step 2 and 3), then predicted quantities would be 1 quarter only.

Step 5 - Update Safety Stock

Lastly, traditional inventory management techniques[5] and best practices could be applied to effectively manage the inventory. These include:

[5] https://www.bigcommerce.com/blog/inventory-management/#inventory-management-techniques

- *Safety stock calculation* – a buffer inventory for fluctuating demand
- *Economic Order Quantity* – ideal amount that might dealership should order for each part every time. Minimum order quantity (min amount that supplier would sell) plays a role in this.
- *ABC Analysis* – classifying parts into A, B and C types based on value and demand.

Data:

- The spares inventory data from the dealership

Use:

- Basic math to calculate traditional inventory measures (mentioned above)

To:

- To effectively manage inventory at the dealership against demand and supply fluctuations.

Frequency of Models Run

- All models in 1a could run for 1 year forecast and refresh quarterly.

Problem 1b – What is the Optimum Service Process?

This part of the problem addresses the optimization of service at the dealership. The key question to address here is that "how can I minimize the cost of labor for my customers while maintaining the customer service level?". Every dealership has a fixed number of certified mechanics who work in the service department. Some mechanics have more or higher-level certification (experts) than others. Some models can only be handled by certain types of mechanics. The number of hours across these mechanics is fixed in each week but a higher-level certified mechanic could complete a job sooner than a lower level one, but they are also expensive. Given these constraints, what is the optimum schedule (who works on what) that gets lowest labor cost to the customer.

Another angle of this is, given upcoming demand of service job (repair and replace), do I need more or less mechanics on the payroll.

Data:

- Expected volume service incidents (from 1a)
- Expected volume of repair and replace jobs (from 1a)
- Mechanics available and their hourly rates
- Dealership service center schedule (how many days open and what hours)
- Mechanics skill mapping – who can work on what type of job and estimated time it takes each of them.
    - All of this data would be available from the dealership's service center.

Use:

- Model 1 – Stochastic discrete event optimization

    - Object function – minimize total number of mechanics in each month
    - Constraints – mechanics hours supply matches demand from service incidents prediction
- Model 2 - Stochastic discrete event optimization
    - Objective function – minimize labor cost for all jobs in each day
    - Constraint – hours not to exceed available mechanic hours in a day

To:

- Model 1 aims to lower the labor cost for the dealership by optimizing the mechanics they should keep on payroll given upcoming demand of service incidents.
- Model 2 aims at lowering the labor cost for the customer by optimizing the schedule of who works on what job (if a higher skill mechanic works on a job, she takes less time but is expensive and vice versa).
- In Model 2, the daily labor cost to the dealership doesn't change (they must pay everybody on shift that day) but the cost to customers could be optimized while maximizing throughput for the day. Whereas model 1 attempts to lower the labor cost for the dealership over longer duration.

Frequency of Models Run

- Model 1 runs monthly (or quarterly) so that dealership can plan for any suggested labor changes.
- Model 2 runs daily so that the dealership can plan the schedule for the day.

Problem 1c – Are the Filed Claims Legitimate?

This part of the problem addresses the legitimacy of the warranty claims issue. Once a vehicle has come into the service department and has made a warranty claim, the repair and part replacement costs are Honda's responsibility if the claim is legitimate. But the warranty program has several eligibility requirements (Section: Warranty Program Overview). If any of these requirements are not met, the claim does not qualify for warranty program. The case says that Honda used to review cases manually and it was at least 1 week worth of time every month. Automating this process with a machine learning model could save a lot of time as well as money (from the ineligible warranty claims).

The methodology being proposed for this problem is that claims should be classified into 4 classes:

1. Incomplete – if any critical information is missing
2. Inaccurate – if any information or claim is inaccurately represented
3. Eligible – everything looks fine and claim is valid
4. Ineligible – one or more warranty provisions are not met

Claim will be rejected for classes 1, 2 and 4. Step 1 will classify claims into Incomplete, Inaccurate & Rest. Step 2 will take the population in 'Rest' class and classify it further into Eligible and Ineligible.

Step 1 – Classify Claims to Incomplete, Inaccurate & Rest

Data:

- Claims data from dealership's service department. This analysis could be run locally at the dealership level or by Honda nationally and then results could be shared with dealerships. This data would include:
    - Model information (type, year, VIN)
    - Mileage
    - Claim information – hopefully this information is captured in systematic form and not free text. Data preparation technique would be needed if this is free text.
- Telematic data from previous maintenance trips.
    - Information on status of parts
    - Service history
- Sales data from the dealership.
    - Who was the vehicle sold to through its life.
    - Vehicle factory specs
- Insurance information
    - To include reported accidents

Use:

- Feature extraction techniques like Bags of Words and ngram
- Regex, missing data and rules-based checks

To:

- Feature extraction would be used if critical information is in free text form.
- Regex, missing data and rules would help check:
    - Incompleteness of fields – E.g. if required fields are empty.
    - Inaccurate data – E.g.
        - If mileage is higher than eligibility criteria for warranty
        - If vehicle age is higher than eligibility (from sales data)
        - If odometer is tempered (from telematic data)
        - If any unqualified parts are used (from telematic data)
        - If any accidents are reported (from insurance data)
        - If improper fueling occurred (from telematic data)
    - All other records would be classified as 'Rest'.

Step 2 – Classify 'Rest' to Eligible & Ineligible

Hopefully step 1 would capture most of the ineligible claims. This step would ensure that if claims slip through, we have another filter to identify potentially ineligible claims.

Data:

- 'Rest' class data from step 1
- Eligible/Ineligible class from historical checks (response variable)
- Same data as step 1 from sales, telematic, insurance

Use:

- Logistic regression

To:

- Predict ineligible claims based on probability. It would give Honda an opportunity to adjust the threshold and determine how many high probability claims do they want to confirm eligibility for. This would take way less time than reviewing cases from scratch.
- Model would learn from the data and responses and attempt to predict ineligible cases, hopefully the ones that do not meet the provisions for warranty.

Frequency of Models Run

- Ideally, this model could be operationalized such that the dealership can perform these checks at the time they are accepting a claim in the service department. This would enable Service Reps to reject a claim immediately and prevent labor & part costs.
- Otherwise, Model in 1c could run on a weekly basis or even daily so that the ineligible cases are identified quick enough to recoup the costs from the customer.

Problem 2 – How to best use CSAT Survey Data?

Problem 2 focuses on the soft cost side of the things. Every customer fills out surveys, mostly online, or in the dealership after most trips (for service or sale). These surveys have nuggets of information that could help Honda improve a whole spectrum of things on their ends. These improvements would improve customer satisfaction in the long run, increase brand loyalty and sales.

The goal from this problem is to identify positive, negative and neutral sentiment from the data and then within each class, determine the trends that are causing the sentiment. These trends could trigger many different initiatives like design improvements, sales campaigns, service process improvements, targeted marketing etc.

Step 1 – Feature Extraction

A lot of data in surveys is typically in free text form. It is critical to convert that data into usable form first.

Data:

- Survey data from Honda or dealership

Use

- Ngrams and Bags of word (BoW)

To:

- Extract features from the free text. This technique outputs a large quantity of features (sparse matrix), thus it has to be made sure that enough data is available for model to not overfit or feature selection methods would have to be employed.

For example, typical BoW output[6] for movie reviews:

	good	movie	not	a	did	like
good movie	1	1	0	0	0	0
not a good movie	1	1	1	1	0	0
did not like	0	0	1	0	1	1

Typical NGram output (where we count pairs, triplets etc.)

	good movie	movie	did not	a	…
good movie	1	1	0	0	…
not a good movie	1	1	0	1	…
did not like	0	0	1	0	…

[6] https://www.youtube.com/watch?v=7YacOe4XwhY&list=PLIG2x2RJ_4LTF-Ilu7-J3y_yg8LRe1WZq&index=2

Step 2 – Sentiment Analysis

In this step, we will take the features from step 1, and classify them into Positive, Negative and Neutral classes.

Data:

- Features from step 1
- Any other features from the survey data
- Positive, Negative & Neutral classes from historical assessment of survey data

Use:

- SVM

To:

- Identify surveys that had positive, negative or neutral comments.

Step 3 – Clustering

Now that we have classified survey data into positive, negative and neutral buckets, trends within each class have to be identified to answer the question that “what causes these customers to say positive/negative/neutral thing?”. The trends from positive class could be doubled down on, trends from negative class could be worked on and trends from neutral class would provide good insights like may be there are initiatives that are not working.

Data:

- Survey data from the dealership or Honda
- Positive, negative & neutral classes from step 2

Use:

- K-Means clustering on each class

To:

- Identify trends and themes within each class.
- Each or top clusters will have to be studied to identify what caused that sentiment.

Frequency of Models Run

- This model would run at least quarterly so that there is enough data to evaluate and there is enough time for on-going initiatives to make an effect on the survey data.

Conclusion

This case has some very traditional but interesting problems and allowed several types of very fundamental and advanced analytics techniques to be employed to provide a solution.

How would the models be combined for cohesive solution?

As seen in the problem solutions in the report, several type of classification and prediction models along with data prep and feature selection techniques are employed to come up with a solution.

What specific data might be needed to use in the models and how it might be collected?

Majority of the data has to come from the dealerships or from Honda, but some data is also needed from the public and partner sources like government, insurance etc. Collection of the data would hopefully be part of Honda's process where they are systematically feeding this data to their central or local data warehouses.

How often it might need to be refreshed and the models re-run?

Different problems need different refresh rate.

- Spares Inventory models – refreshes quarterly
- Service Process models – two models – one runs daily, one monthly
- Claim Eligibility models – daily or at least weekly
- CSAT Survey models – quarterly

As Prof. Joel Sokol has repeatedly during the course, analytics modeling is as much of an art as it is science. The proposed combination of models would provide great suggestions at times and would digress at others. Human intervention would be needed to keep checking model's performance and most importantly interpret the outputs of the models.