Veterinarian Hospital Wait Time Estimator

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https://amodavis.github.io/

Abstract

This project was requested by a veterinary hospital to address wait times. They are unable to estimate how long a patient is expected to wait due to urgent cases that come in and require special attention. Currently, staff just provides a wild guess on how long the wait will be. The intent of this project is to demonstrate a use case in supervised regression. In it, you will see the problem defined and business objective set. I will guide you through my research and methodologies, resulting in a usable wait time estimator.

Veterinarian Hospital Wait Time Estimator

Veterinarian clinics struggle with wait times. These clinics are unique since they provide specialized services, as well as emergency care for pets. Those with appointments often take a backseat to urgent cases. There are also unknown factors with appointment length and the staff required for each case since many are unique. Agrawal (2017) compares the operation of a hospital to that of an airport and poses several ways that operations can be streamlined. The key is to collect data at every point, so you can take advantage of machine learning.

The pandemic has increased pet ownership, causing the sheer volume of appointments to increase, both in-person and over the phone. Shannon (2021) indicates the more people are at home with their pets, the more likely they are to notice problems. This increases the need for veterinary visits. However, with the onset of the pandemic came closures and changes in protocols, limiting the number of appointments available at routine vet offices. This forces some owners to take their pets to the ER for what might normally be a routine office visit (Mechanic, 2020). Longer wait times at the veterinarian hospital can also be attributed to miscommunications that can occur over remote communication between the vet and pet owners. Face-to-face interaction at your normal vet clinic can often resolve problems before they escalate (Dock, 2020).

So, what is a reasonable wait time? Shupe (2015) shows results from a survey indicating that most pet owners start to get upset after 15 minutes. He also makes recommendations on how to reduce stress levels during the wait. Interestingly, "Create technical interactions to keep clients focused on milestones" is second on that list, which is where an estimated wait time can help. Batt & Terwiesch (2015) highlight a notion that we have all experienced. Patients do not like being skipped. In clinics, it is not first come, first serve. A critical case, which may not always be apparent, is likely to be pushed forward in the queue. The activity in the waiting area is often not reflective of the activity in treatment areas. That perception can have a negative effect.

Method

Business Problem

The demand for emergency treatment of pets has created a backlog in veterinarian hospitals. Although facilities are staffed 24 hours 7 days a week, they are unable to keep up the pace. Customers have to wait with their pets an uncomfortable amount of time. Customers get impatient waiting for their scheduled appointment time and don't know how long they can expect to wait.

Business Objective 1:	*Let clients know anticipated wait time.*
Business Objective 2:	*Understand factors that contribute to longer wait time so they can be mitigated*

Data Sources

I received three spreadsheets of data from an active veterinarian hospital. The first dataset reflects snapshots of the two waiting areas in 5-minute increments. The second dataset includes details of a patient's appointment, such as appointment time and symptoms, by department. Unfortunately, many triage and treatment codes, although standardized, were left blank. The third spreadsheet was an export from a wait time estimator known to be inaccurate and not customized to the facility or domain. Due to the known inaccuracies, I did not utilize this final dataset. The only commonality of the data from the waiting areas and the patient records was time. In addition to datetime data, there are also categorical consultation codes and appointment types. Since data from multiple appointments were stored in the same data fields in the same record in the patient dataset, I used Trifacta to split the data into separate fields.

Unfortunately, I did not receive patient wait times. Rather, I received patient check-in times and running counts of patients in the waiting room. There was a lot of missing categorical data. It appears these fields are not required when making an appointment or to complete the check-in process. There was also a lack of event tracking. Even without pre-determined wait times, I expected to compute wait times based on check-in, treatment, and check-out times, however these event times were not provided. There was a disconnect in the time intervals provided in the waiting room whiteboard data. Most checkpoints were approximately five-minute intervals but not exactly. This made it more difficult to associate waiting rooms to patient appointments.

Since this dataset is from a current, operating animal hospital, I will not post the data. No personal patient information is included, and the clients are animals, so the data are not considered Protected Health Information (PHI). Aggregated data are viewable in visualizations provided in the results section.

Exploratory Data Analysis

Both R and Python were used to prepare data for the initial statistical analysis and visualizations. This allowed me to get to know the data and the available features. I reviewed datasets to determine data types and volume of data. Distributions were analyzed and correlation between features determined. I analyzed descriptive statistics to identify outliers and anomalies. PowerBI was used to demonstrate responses to specific questions which allowed me to focus on features in which the clinic expressed specific interest.

Technical Approach

The biggest question remained with how to train a model to calculate wait times when only appointment times were provided. Troccoli, et al. (n.d.) used multiple methods to approach the problem of wait times. You can treat the target variable as continuous creating a regression problem, or you can set up "buckets" of time as categorical target variables for a multi-classification problem. Perception of time can have a powerful impact, both positively and negatively.

So, how do we calculate wait time? Without timestamps for each stage in the process (check-in time, treatment time, check-out time), I am unable to accurately compute wait times. I changed my modeling objective to "Predict how many cases, given triage types, are treated concurrently in a given 5-minute waiting room window." For example, if cases of triage types 1, 2, and 3 are being treated, 5 total patients can be treated at one time.

This capacity can then be used to calculate waiting time, using Little's Law. Little's Law states that the average length of a line (L) is the product of the waiting time in line (W) multiplied by the throughput to the system (Lambda) (Kosven, 2019).

$$L = W\lambda$$

or

Wait Time (min) = People Waiting/ Number Concurrent Cases treated (Predicted by Model)

I originally approached this problem as a multi-class classification problem with wait-time buckets. However, after I changed the approach to calculate throughput with the data provided, this turned into a regression problem using the throughput of patients as the target variable. I created a new derived column to store the patient change per interval to represent the throughput of the treatment area.

Modeling Objective: Perform supervised learning to predict patient throughput

Using Python, I compared three different regression models: Decision Tree Regressor, Random Forest Regressor, and an AdaBoost Regressor. The advantage of tree models is the ability to explain the features impacting wait, which was a secondary objective of the customer. To assess model performance for each, data was split into training and validation datasets. Models were then assessed using the coefficient of determination (R^2) to explain variability. The best performing model progressed to the tuning phase, where multiple hyperparameters were adjusted to optimize R^2. For model deployment, I used Python to create a small application to prompt for contributing attributes. The estimator accepts current patient counts from the waiting areas and treatment rooms and provides an estimated wait time for newcomers.

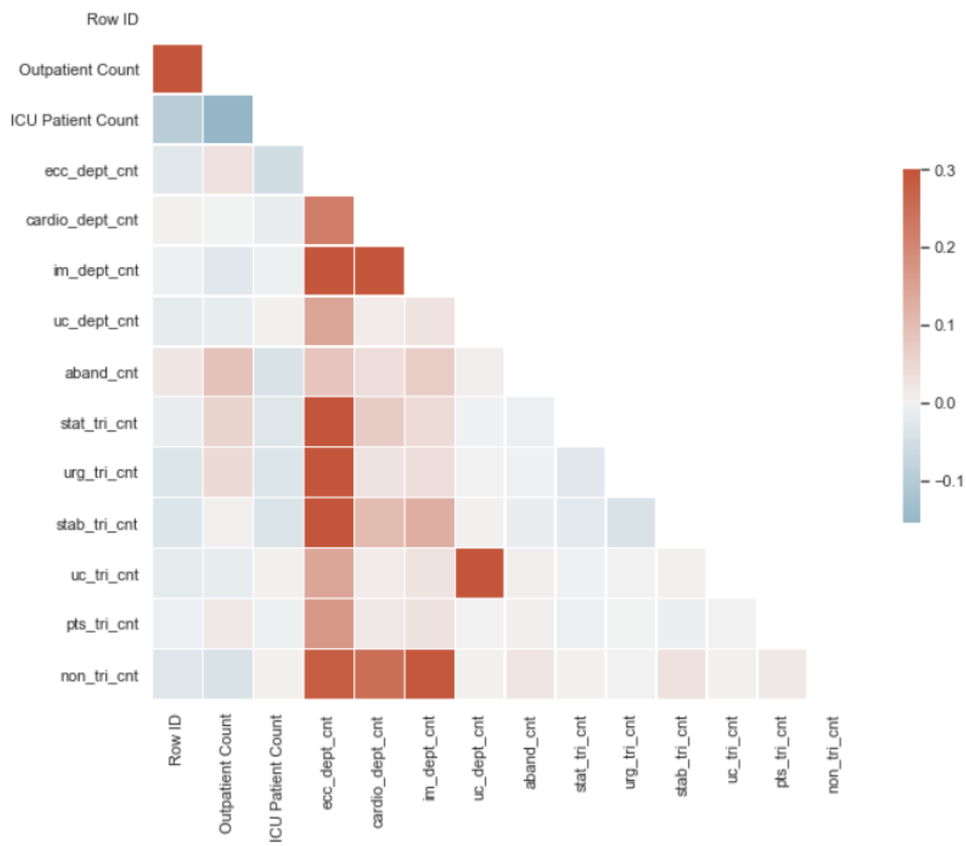
Results

Exploratory Data Analysis

I was surprised that the volume of patients at the veterinarian hospital did not drop at the onset of the pandemic, nor did it peak. This demonstrated that animal emergencies, which are normally lower in March, remained at their usual level, despite shutdowns at many places. Veterinarian hospitals, like human hospitals, do not shut down, and their workers were considered essential to provide imperative treatment during the pandemic. However, trips to the animal hospital did begin to increase in July 2020, and the increase has yet to drop back to pre-pandemic levels.

When reviewing abandonment data, I was pleasantly surprised to find the distributions represented to be normal, for both Outpatient and Intensive Care Unit (ICU) waiting areas. Although, I was shocked to see that anomalies for the number of patients waiting in the outpatient waiting area ranged from 60 to over 100 patients.

There was an outlier identified reviewing Emergency Critical Care (ECC) counts. The maximum value of patients in that department per waiting room count was 73. Upon reviewing the data, I identified an almost 24-hour gap in the whiteboard data, which resulted in all patients treated during that time to be assigned to the last whiteboard entry. This outlier record was removed. No features were overly correlated, so they were all retained for use in training the model.

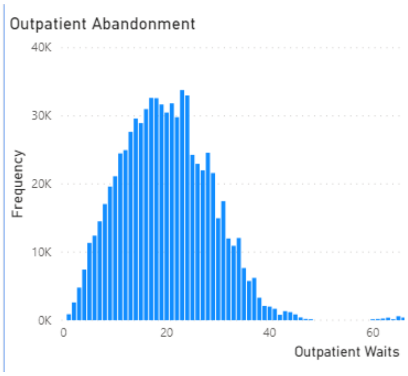


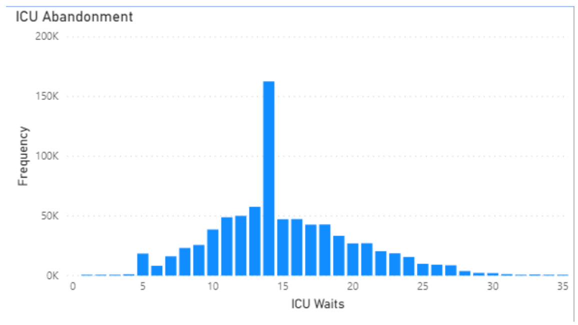
Research Question Visualizations

PowerBI visualizations were used to review features in which the hospital expressed interest. I held a meeting with hospital IT personnel to understand some of the areas of concern. I also paid particular attention to possible causes brought up in an article by Union Lake Veterinary Hospital (2018). In it, typical causes of wait times at the vet were suggested, such as emergencies, late arrivals, nervous patients, and difficult diagnoses.

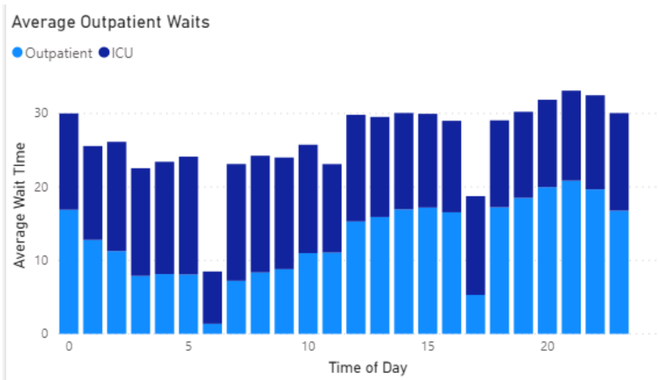
- How many patients in the waiting room when a customer leaves?

Outpatient waits for abandoned appointments is normally distributed with outliers of 68 or more people waiting. The peak abandonment in the outpatient waiting area occurs when 23 patients are already waiting. ICU waits for abandoned appointments is also normally distributed, peaking at 14 patients.

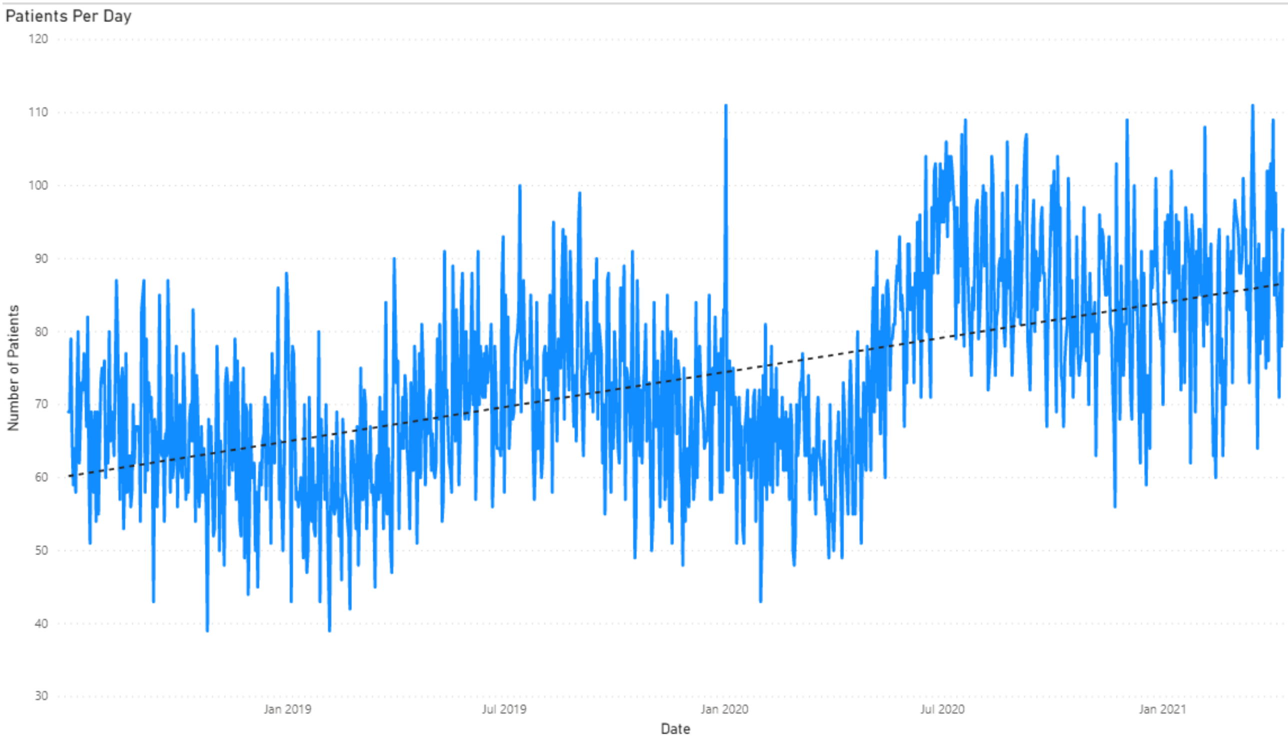




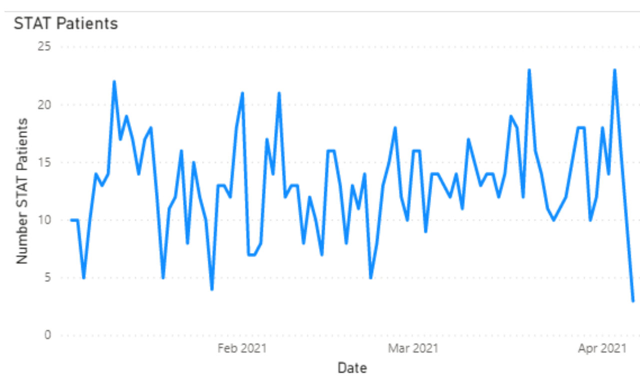
- What is the average patient count in the waiting room during normal office hours?
- When are the best/worst times to book an appointment?



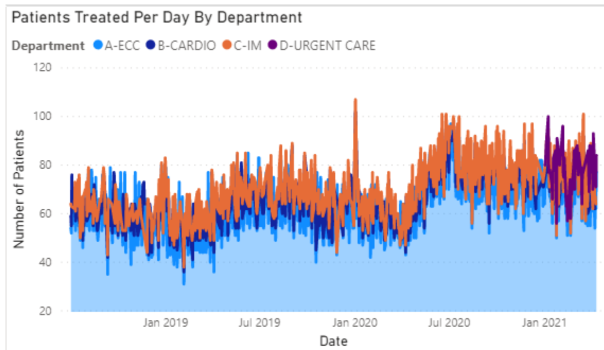
- Has there been an increase in the number of patients waiting since the pandemic?



- How many urgent (“stat”) cases are seen a day?



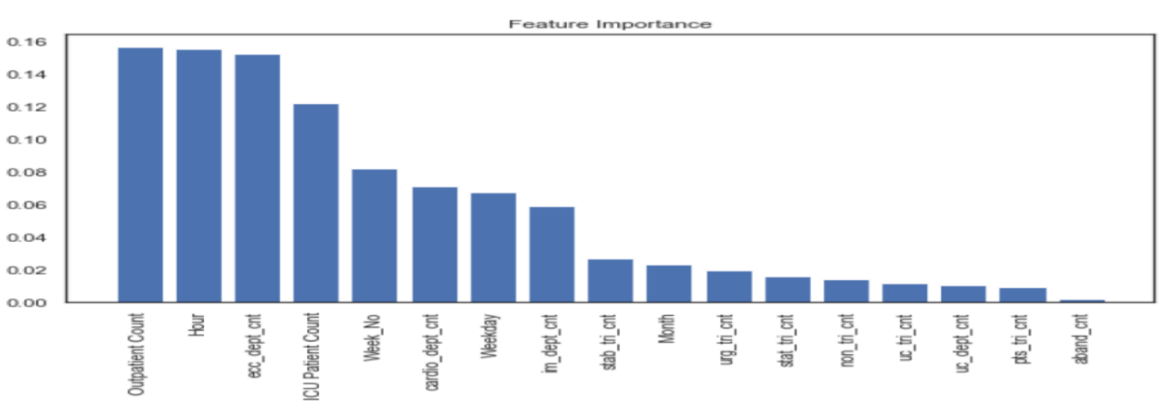
- What is the maximum/average/minimum number of patients treated in each department per time window?



Modeling

Scikit-Learn's Decision Tree Regressor was selected for its explainability. There was no need to encode or scale data before training decision trees. Mean Absolute Error (MAE) was used for the decision metric, since we are not concerned about smaller errors. The initial model resulted in a coefficient of determination of -0.38, which is considered a weak model.

Using Scikit-Learn's Random Forest Regressor resulted in a coefficient of determination of -0.10, which is a poor model, even after restricting to important features only. However, an advantage of a random forest model is its ability to relay the features having the most impact on the model. This allowed me to further refine features used in all models. The AdaBoost Regressor did not perform much better with a coefficient of determination of 0.2.



Due to its initial performance, I selected the decision tree model to tune further. Limiting features increased the coefficient of determination from -0.38 to -0.44. Changing the criterion metric from MAE to Poisson increased R^2 further to -0.49. Selecting the best random split increased it to -0.51. Considering the square root of the number of features at each decision point increased R^2 again to -0.59. This provided a feasible model with a moderate rating. The resulting tree was quite complex, although it decreased from a depth of 51 with 4252 branches to a tree depth of 32 with 3970 leaves.

The deployed estimator application prompts for the specific status of both the waiting areas and treatment areas to provide an estimated wait time. See a sample of the estimator below.

```
Enter number of patients currently waiting in the Outpatient Waiting Room 12
Enter number of patients currently waiting in the ICU Waiting Room 12
Enter number of patients checked in for the ECC Dept 1
Enter number of patients checked in for the CARDIO Dept 1
Enter number of patients checked in for the IM Dept 0


Throughput is expected to be 8 patients per hour.
Current wait time is estimated to be 182 minutes.
```

Discussion

Limitations

This project was limited by the dataset provided. Without known wait times and patient severities for all records, the accuracy and scalability of the model is limited. See recommendations below. Due to several missing fields, only about 4 months of data was usable. This did not provide the volume of data needed to accurately train a model. Time was also a limitation. This was a short 4-week sprint. A lot of time was spent estimating throughput, limiting time that could have been spent on natural language processing.

Future Recommendations

There are a few recommendations I have that are essential before the model can be improved to a deployable state. Most of these recommendations are related to data collection. The model can only be as accurate as the data on which it is trained.

1. Start collecting data at each checkpoint. Log the times when a patient checks in, is sent back to the treatment room, is consulted by the vet and/or assistant, and when the patient checks out. This is imperative to determine where wait times are most affected.
2. Require presenting problem and therapeutic procedure data fields to be entered. These data are essential to correlate wait times with various types of procedures. Although it appears that descriptions are standardized, they are often left blank. There is likely a billing system that has more detailed procedure data that could be linked.
3. Categorize clinical descriptions. Descriptions of problems reported are entered free form. Although notes can provide added detailed required for treatment, it would be helpful to categorize the problems reported. For example, a multiple choice of common ailments can be selected from a dropdown list.
4. For future models, I recommend using natural language processing to pull out commonly used words and frequency from both patient descriptions and vet treatment notes. These could also be used to determine commonalities impacting treatment times for each case.

Conclusion

While we want to take care of our pets, we are also trying to minimize the time spent indoors in public, like a waiting room. If a clinic can provide an estimated wait time for their clients, they could spend that time outside with the pet until they are closer to getting called back for their examination, or safely wait in their cars.

There are several studies that show that customers are more patient when given an estimated time upfront. They can better plan their day and are more likely to bring their pet in for routine checkups. Animals who are ill are often anxious. This anxiety is passed to their owner. Providing an estimated wait time in such a case can bring that anxiety down. When a pet owner is calm, their pet will also be calm, and vice versa.

Yu (2021) tells us "Americans spend roughly 37 billion hours each year waiting in line," so we are used to waiting. However, we would like to know how much patience to bottle up.

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Appendix A

Presentation Q&A

1. What factors were considered when determining wait times?
2. Why did you select a regression model?
3. Do you think a model with an accuracy of 0.59 is deployable?
4. How will you determine if the estimated wait times provided to patients are accurate? Is there a feedback mechanism?
5. Is the patient expected to count the number of patients in the waiting room?
6. Why is it necessary to enter the number of patience being treated in each department?
7. How did you handle null values?
8. Why do you think there are less patients waiting at 0600 and 1700?
9. What do you think caused the spike in patients on 2 Jan 2020?
10. Why are there no urgent care patients until 2021?