FINAL PROJECT BIA 6315

Time Series Analysis of Animal Control Intake

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Introduction

For my project, I am tapping into my background with animal sheltering organizations. I will apply time series analysis and forecasting to the intake of stray animals into a shelter.

In the last decade, Austin, Texas has dramatically improved the live release rate of animals under its care. Austin Animal Control is one of the largest animal shelter operations in the country, caring for more than 16,000 animals annually. Part of this transformation is a commitment to transparency, so the city makes data about its operations widely available and is of a volume where statistical analysis may be worthwhile. Furthermore, Austin is a city with outstanding results that may be an excellent model to understand and potentially emulate.

Being involved in animal sheltering, I have often heard about a phenomenon called "kitten season." Every spring, there is a significant spike in kittens entering shelters. This is related to the reproduction cycle of cats that kicks into gear as daylight starts to increase after the winter solstice (December 21st or 22nd) and kittens begin arriving in April. This continues through the summer until feline reproduction wanes as sunlight decreases approaching the vernal equinox (September 21st).

I am curious how pronounced "kitten season" will be in the data and if there are any interesting patterns in the intake of stray dogs.

Statement of Business Problem

The goal of my project is to develop a twelve-month forecast for the intake of stray animals given about 6.5 years of historical data.

For animal shelters, this is essentially a demand forecast central to the operation of the organization. The volume of animals coming into a shelter drives the vast majority of variable costs such as food, staff/volunteer hours to care for animals, and medicine such as vaccinations to protect individual animals and as well as to prevent the spread of disease within the population of shelter animals.

The flow of animals coming into the shelter over the year is also essential to understand, so the organization is adequately prepared to care for the animals. For example, is the flow roughly steady month-to-month or are there natural peaks and valleys where the organization needs to dial up or down capacity to meet demand.

Most animal sheltering organizations typically look at what happened last year and make educated guesses to budget and prepare for the upcoming year. My project will assess whether time series analysis can produce a more accurate forecast.

Data Sources and Data Description

I obtained the data for this project from the City of Austin's open data portal on the "Austin Animal Center Intakes" data set page. (https://data.austintexas.gov/Health-and-Community-Services/Austin-Animal-Center-Intakes/wter-evkm)

Data for the intake of animals into the shelter is available from October 1, 2013 to the present and is updated daily by Austin Animal Center. The data set contains an observation for every animal that enters the shelter and about a dozen attributes, to include:

- The ID assigned to the animal.
- The name of the animal, if known.
- Date and time of intake into the facility.
- Found Location – sometimes a street address, intersection, or just "Austin"
- Intake Type – Stray, Owner Surrender, Euthanasia Request
- Intake Condition – Normal, Injured, Sick, Feral, Aged, Nursing, Pregnant
- Animal Type – Dog, Cat, Bird, Livestock, Other
- Sex upon Intake – Female (Intact or Spayed), Male (Intact or Neutered), Unknown
- Age upon Intake – Number and units (e.g., 3 months, 1 year, 5 years)
- Breed – for dogs (e.g., Pit Bull, German Shepherd), for cats (e.g., Domestic Short or Long Hair), Other/Wildlife (Bat, Racoon, Opossum, etc.)
- Color – the single or mixed color of the animal's fur.

I focused on the largest portion of the data set - cats and dogs entering the shelter as strays, which is about 70% of the 120K observations for October 2013 through August 2020.

I ended up limiting the data to the end of February 2020. There was an unusual drop in intake starting in March as "stay at home" orders went into effect to flatten the curve of the COVID-19 pandemic. Some animal shelter services are deemed essential such as caring for sick and injured homeless pets or controlling dangerous animals. But veterinary clinics also needed to preserve personal protective equipment and medical supplies that could be repurposed to care for humans, if needed. Thus, animal shelters were required to curtail all non-essential activities.

This left data on 80,337 cats and dogs entering Austin Animal Center as strays from October 2013 to February 2020. To create a time series, I aggregated the data to monthly intake of cats and dogs across 77 months (or 6 years and 5 months).

Exploratory Data Analysis

Descriptive Statistics

Table 1 presents the descriptive statistics for the monthly intake of cats and dogs between October 2013 to February 2020. Figure 1 contains histograms and boxplots of the distribution of cat and dog intake.

Figure 1 - Histograms & Box Plots

Table 1 - Descriptive Statistics

	Obs.	Mean	Median	SD	Range (Min, Max)	IQR (Q1, Q3)
Cat	77	440.13	439	215.15	808 (162, 970)	358 (230, 588)
Dog	77	603.21	601	56.04	264 (505, 769)	66 (563, 629)

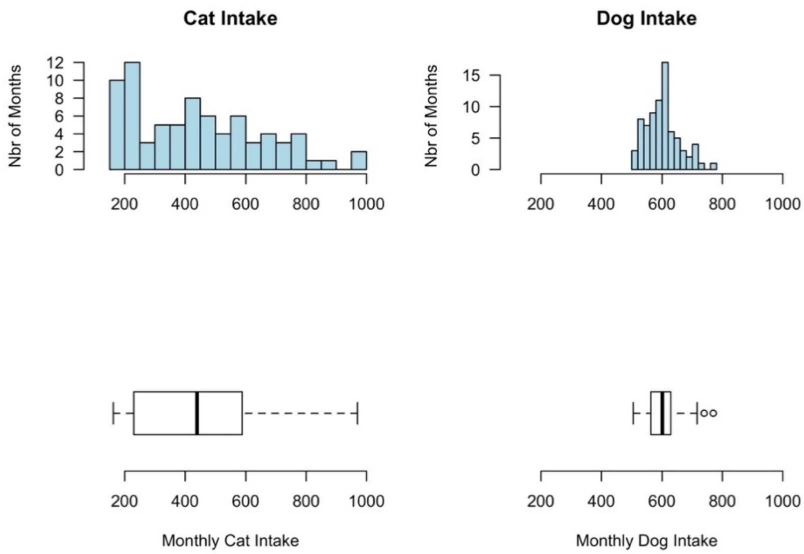

Figure 1 - Histograms & Box Plots

The initial takeaway is that there is more variation in the monthly cat intake than dog intake. The standard deviation, absolute range, and interquartile range are all much larger for cats than dogs. Dog intake averages around 600 plus or minus 50-60 dogs per month. Cats have a lower average of 440, but a quarter of the months, we see under 230 cats and another 25% of the months we see over 590, up to a maximum of nearly 1000 cats entering the shelter per month.

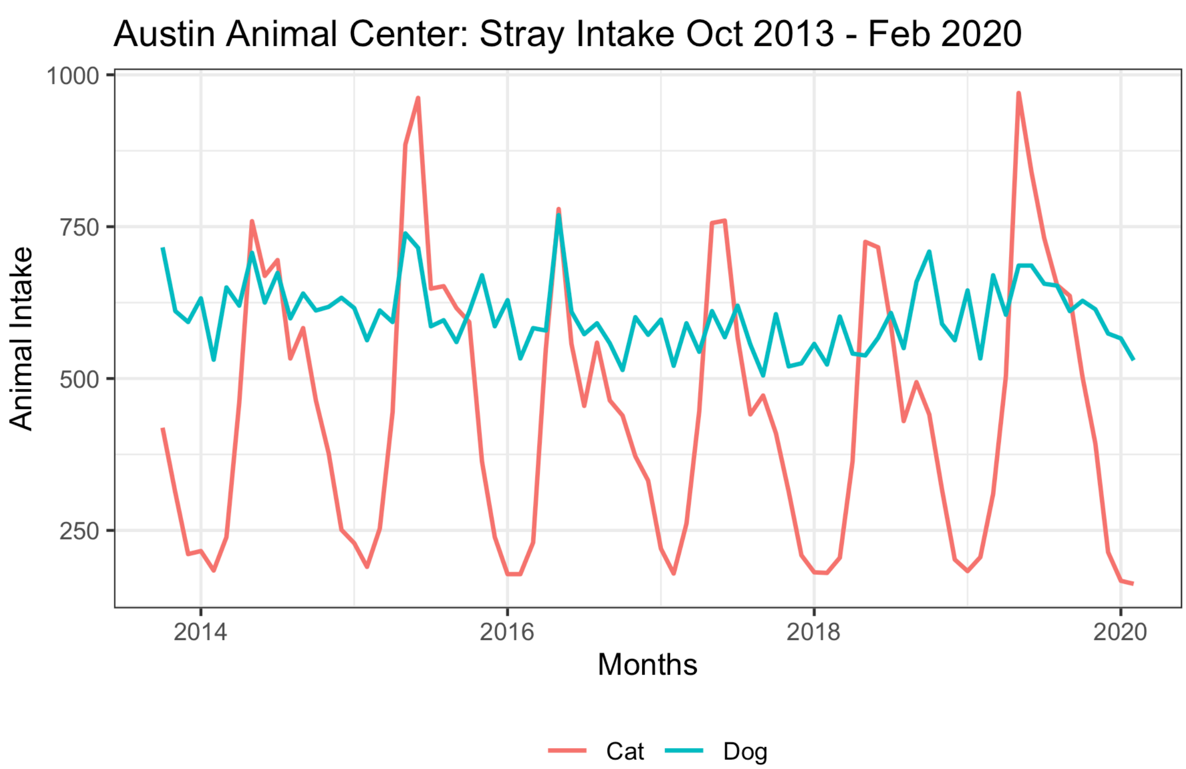

Figure 2 - Time Series Plot of Cat & Dog Intake

Time Series Components

Figure 2 contains a time series plot showing the monthly intake of cats and dogs as separate series on the same scale as the events unfolded over time.

The time series plot reinforces there is more variation in cat intake compared to monthly dog intake. The dog intake bounces up and down but hovers around the average of 600 dogs per month. On the other hand, there are prominent peaks and valleys in cat intake. There is a difference of nearly 600 cats between the lowest and highest intake months. January and February are the lightest months, with a sharp increase to the high point in May or June (AKA "kitten season") and a steady decline through December. From this plot, it is unclear if there is a seasonal component for dog intake.

I used "Seasonal and Trend decomposition using Loess (STL)" to separate and examine the typical components of a times series – Level, Trend-Cycle, Seasonality, and the remainder (or noise). The components are typically plotted separately, but I found it useful to plot several components on the same scale as the original time series and examine the seasonal component in isolation.

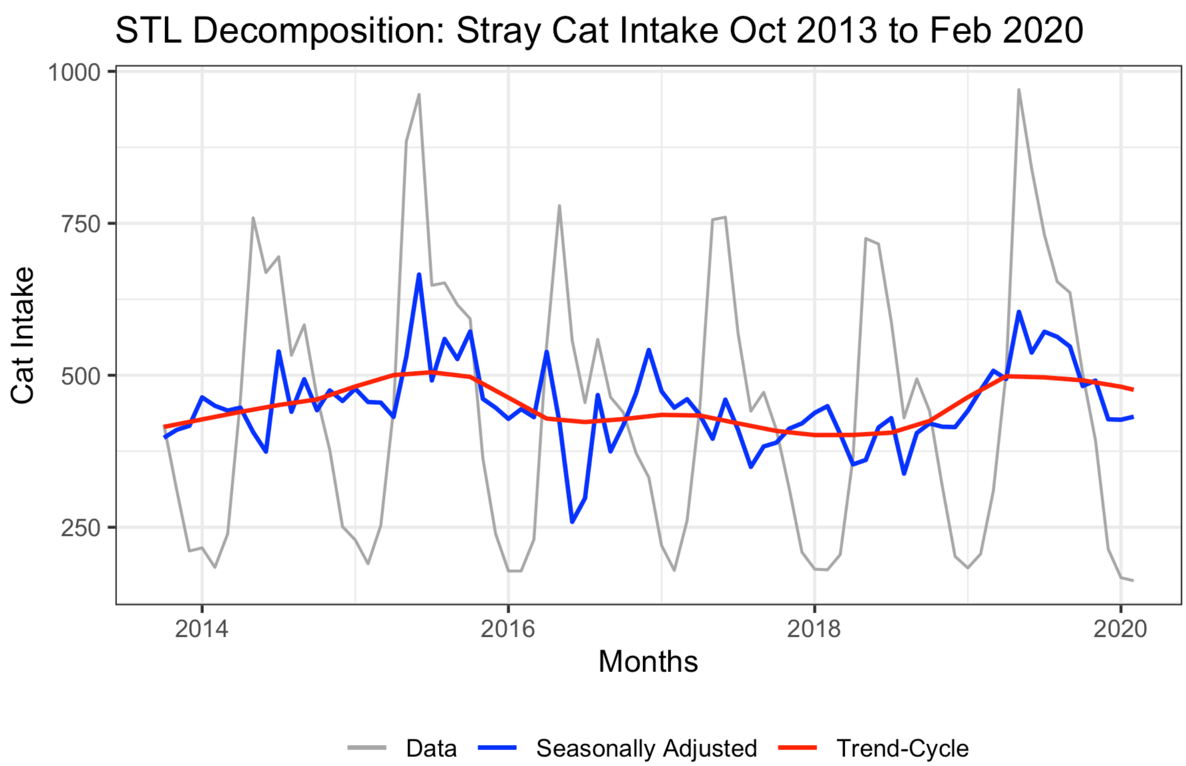

Figure 3 - STL Decomposition of Cat Intake

Figure 3 illustrates the decomposition for cat intake. The light gray line is the original time series, the red line is the overall trend-cycle in the time series, and the blue line is the seasonally adjusted data. The seasonally adjusted data is the original time series minus the seasonal component. Another way to think about it is that the blue line is the trend (red line) plus the noise or remainder (the ups and downs around the red/trend line). The trend is relatively stable, some years (2015 & 2019) are slightly higher than others (2014, 2016, 2017 & 2018), but there is no strong upward or downward trajectory in the data.

I notice in Figure 3 that the seasonally adjusted series (blue line) occupies a small section in the middle of the original data series, so it alone does not capture much of the volume of cat intake. This indicates that seasonality plays a significant role in the cat intake time series.

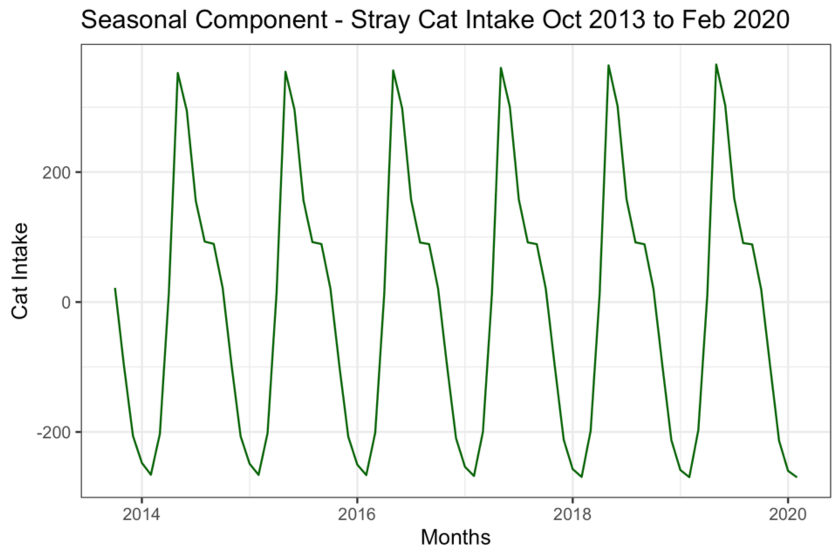

Figure 4 - Seasonal Component of Cat Intake

The seasonal component is plotted separately in Figure 4. It is centered on zero and illustrates the relative difference in the months from a baseline. One thing to note is that the seasonal component is very consistent in cat intake. There is very little, if any, change in the shape of the seasonality from year to year. This is not always the case. Although the basic shape/cycle is the same, in some time series, the cycle's height may grow or shrink at different points in time.

Figure 5 plots the components of the dog intake time series. Be aware of the difference in the scale of the y-axis between the cat and dog plots. For the dog plot, the y-axis ranges from 550 to 775, whereas the cat plot ranges from 200-1000. The narrower range of the y-axis makes the change in the dog intake trend appear to be more pronounced. But as with the cat plot, the dog intake trend is relatively stable, with some years above 600 and some below, but there is no consistent upward or downward trajectory. The seasonally adjusted component (blue line) more closely mirrors the original dog intake time series. This indicates that seasonality plays a smaller role for dog intake.

Figure 6 illustrates the seasonal component of dog intake. Separating the time series components makes it more apparent that there is a seasonal pattern to dog intake. The low is in February, and the high point is in May, but it is not as smooth of a climb or descent as with cat intake. That is some months increase, followed by a subsequent month that declines. Also, note that the height of the seasonal component shrinks a bit in the later years. May's peak is about +80 in 2014 and declines to a height of about +65 in 2019. So, the seasonal component of dog intake is changing slightly over time.

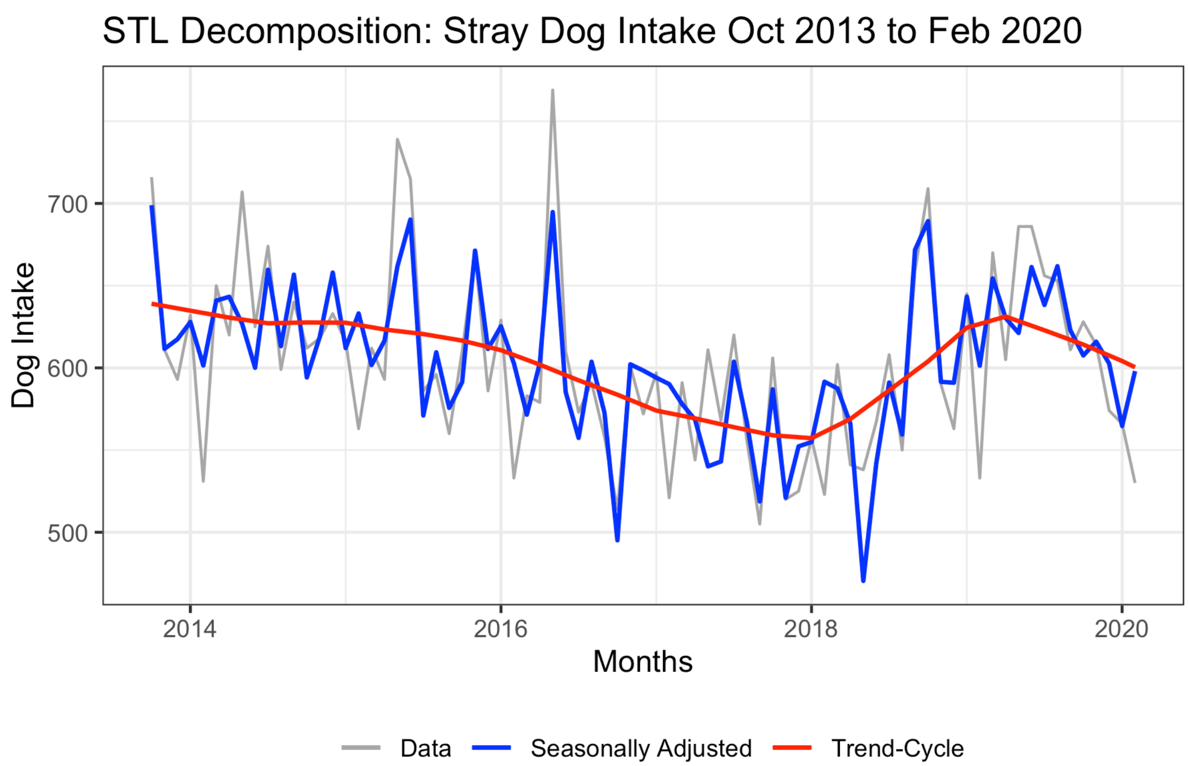

Figure 5 - STL Decomposition of Dog Intake

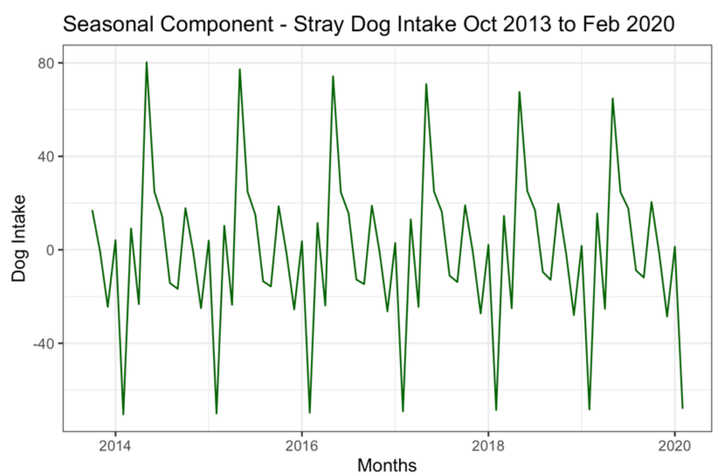

Figure 6 - Seasonal Component of Dog Intake

Time Series Modeling

Introduction

I started with establishing a baseline or benchmark with a simple forecasting method. Both cat and dog intake contain a seasonal component; hence the Seasonal Naïve forecast is the most appropriate benchmark.

I considered linear regression models with seasonality and several flavors of a trend component, and I also experimented with Holt-Winters exponential smoothing.

I held out the last full year (March 2019 to February 2020) as a test data set to assess the models' forecasting accuracy. I used the remaining 65 months (or 5 years and 5 months) of data to train the time series models.

In Table 2, I summarize the key metrics of the various models. The benchmark method is listed first, and then the models are ordered by root mean squared error (RMSE) (best to worst). There were consistently outliers in the model residuals (large errors), so the RMSE metric is usually more reliable in these situations. I highlighted in green the model I believe is the best candidate for each time series.

Table 2 - Time Series Model Metrics

	Type	Model	RMSE	MAE	MAPE	Adj R^2
Cat Intake	Benchmark	Seasonal Naive	131.9	111.0	21.0%	
	Regression	Seasonality	96.1	81.5	15.9%	0.89
	Smoothing	Holt-Winters	97.3	81.7	18.6%	
	Regression	Seasonality with Polynomial Trend	105.9	95.1	30.3%	0.91
	Regression	Seasonality with Linear Trend	125.0	106.0	19.1%	0.89
Dog Intake	Benchmark	Seasonal Naive	78.3	66.3	10.3%	
	Regression	Seasonality	41.1	32.3	5.0%	0.20
	Smoothing	Holt-Winters	42.6	32.5	5.1%	
	Regression	Seasonality with Polynomial Trend	44.7	36.4	5.7%	0.37
	Regression	Seasonality with Linear Trend	71.0	64.0	10.1%	0.34

Discussion of Models for Cat Intake

The **Seasonal Naïve** time series forecasting method, which just relies on last year's cat intake as an estimate for this year's intake, resulted in an error on average of about 132 cats per month. Thinking back to the descriptive statistics, this is an improvement over just using the monthly average of 440 cats with a standard deviation of +/- 215 cats per month.

Regression on Seasonality

Since the cat intake appeared to have a strong seasonal component, I began with a regression model just on seasonality without any trend component. The Adjusted R^2 is 0.89, indicating that the seasonal component explains 89% of the variation in the data! Applying the model to the test data set and forecasting the next 12 months results in a RMSE of 96.1. On average, the forecast may be off by 96 cats per month, which would beat the benchmark's error by 27%.

Table 3 presents the coefficients for this regression model. The reference month is January. The intercept and many of the dummy variables for the remaining months (Feb to Dec) are highly statistically significant.

The Forecast table, which is rounded to a whole number of cats, illustrates in January that the forecasted cat intake is equal to the (Intercept) or 201. For February, the coefficient indicates we expect 15 fewer cats than in January (or 201 – 15 = 186). For March, the coefficient suggests we expect about 36 more cats taken into the shelter than in January (or 201.17 + 36.43 = 237.6), and so on.

Table 3 - Coefficients & Forecast for Cat Regression on Season

Variable	Estimate	Std. Error	t value	Pr(> |t|)	Signif.
(Intercept)	201.17	28.11	7.16	2.5E-09	***
Feb	-15.00	39.75	-0.38	7.1E-01	
Mar	36.43	41.69	0.87	3.9E-01	
Apr	251.63	41.69	6.04	1.6E-07	***
May	579.63	41.69	13.90	< 2e-16	***
Jun	531.63	41.69	12.75	< 2e-16	***
Jul	389.63	41.69	9.35	8.5E-13	***
Aug	321.83	41.69	7.72	3.1E-10	***
Sep	324.63	41.69	7.79	2.5E-10	***
Oct	259.83	39.75	6.54	2.5E-08	***
Nov	141.33	39.75	3.56	8.0E-04	***
Dec	39.50	39.75	0.99	3.2E-01	

Forecast	
Month	Cat Intake
Jan	201
Feb	186
Mar	238
Apr	453
May	781
Jun	733
Jul	591
Aug	523
Sep	526
Oct	461
Nov	343
Dec	241

The regression model considered the 65 months of training data and estimated the value of intake for each month of the year, minimizing the error in the model. Regression creates a fixed or constant definition of the seasonal component that does not change over the life of the time series. This is visible in Figure 7.

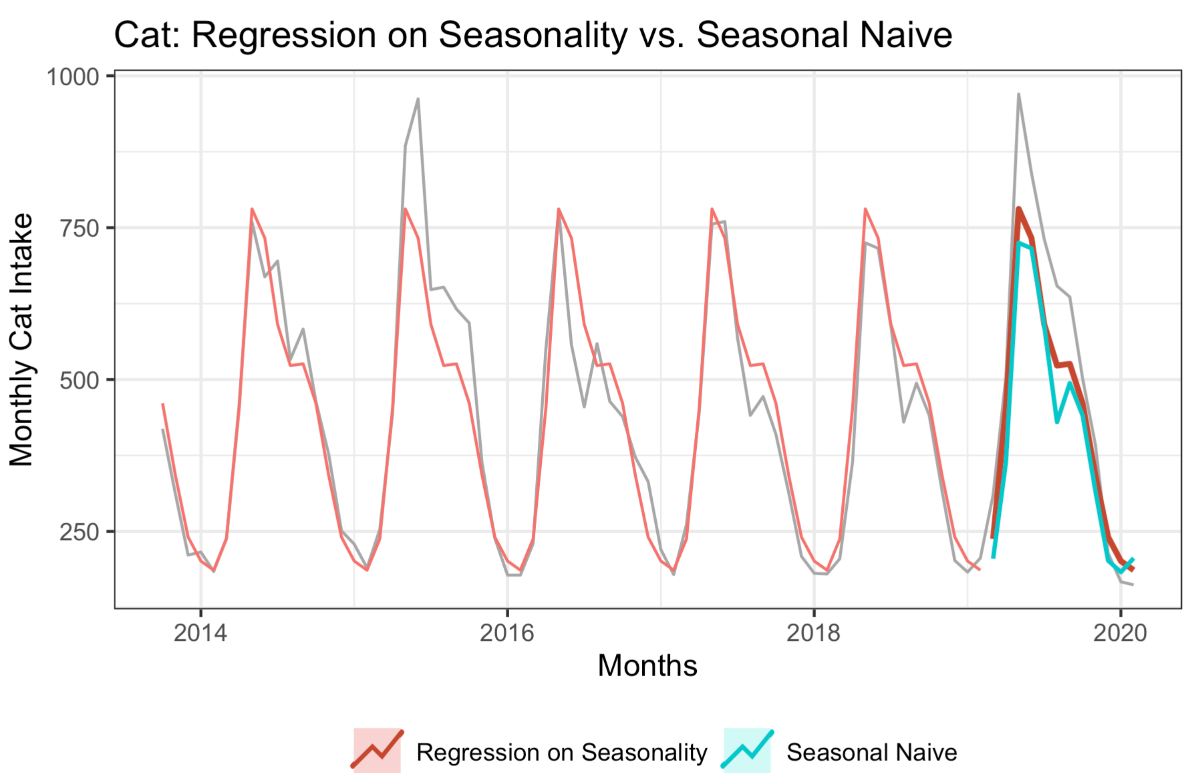

Figure 7 – Regression on Seasonality compared to Seasonal Naïve Forecast

The light gray line is the original cat intake time series. The thin red line up to about 2019 is the regression model's fitted values. For the most part, the fitted values (thin red line) are very close to the actual intake (gray line). But also notice each 12-month cycle is identical and matches the forecasted values presented in Table 3. The thicker red line on the right-hand side is the forecasted values for the test set or the next 12-month period in the future. The forecast just projects the regression's seasonal cycle forward one year. For comparison, the light blue line is the Seasonal Naïve forecast. If you look closely, you will see it is identical to the prior 12-month period (gray line).

Other Regression Variations

Attempting to improve the seasonal regression model, I experimented with adding trend related predictors.

When I added a linear trend, the predictor variable was not statistically significant and RMSE increased to 125 (vs. 96 on the season only model) on the test data set.

The time series' trend component appeared a bit like a third-order polynomial function. So, I included a cubic trend in the model with the regression equation below:

$$Cat\ Intake = \beta_0 + \beta_1\, Season + \beta_2\, Trend + \beta_3\, Trend^2 + \beta_4\, Trend^3$$

The Adjusted R^2 improved slightly to 0.91, but RSME increased to about 106 (rather than 96 with the season only model). I felt this was trying to be too clever. Unless I had a good rationale for why cat intake would exhibit some flavor of a cubic trend, I was likely simply overfitting the training data and would not produce a reliable forecast.

Holt-Winters Exponential Smoothing

Exponential smoothing is essentially a weighted moving average technique where the weight decays exponentially as we move further back in time. Smoothing parameters define how much weight is given to the most recent values versus more distant past values in the time series. A large value (closer to 1) more heavily weights the most recent observations and adjusts to short-term trends in the data. A smaller smoothing parameter value (closer to 0) carries forward the impact of older observations, and the forecast adapts more slowly to changes or reflects longer-term trends in the data.

Holt-Winters smooths three different components:

- Level – the general location of the time series on the y-axis.
- Slope – describes whether the series overall is trending upward, downward, or remaining approximately flat.
- Season – the shape of the seasonal cycle, which can adjust or change over time.

The Holt-Winters technique applied to cat intake resulted in the smoothing parameters presented in Table 4. I find it easier to interpret the smoothing parameters and impact on the fitted values visually. Figure 8 shows the Level, Slope, and Season components of the cat intake training data after they have been smoothed by the given parameters.

Table 4 - Smoothing Parameters for Cat Intake

Component	Parameter	Value
Level	alpha	0.337
Slope	beta	0.009
Season	gamma	0.296

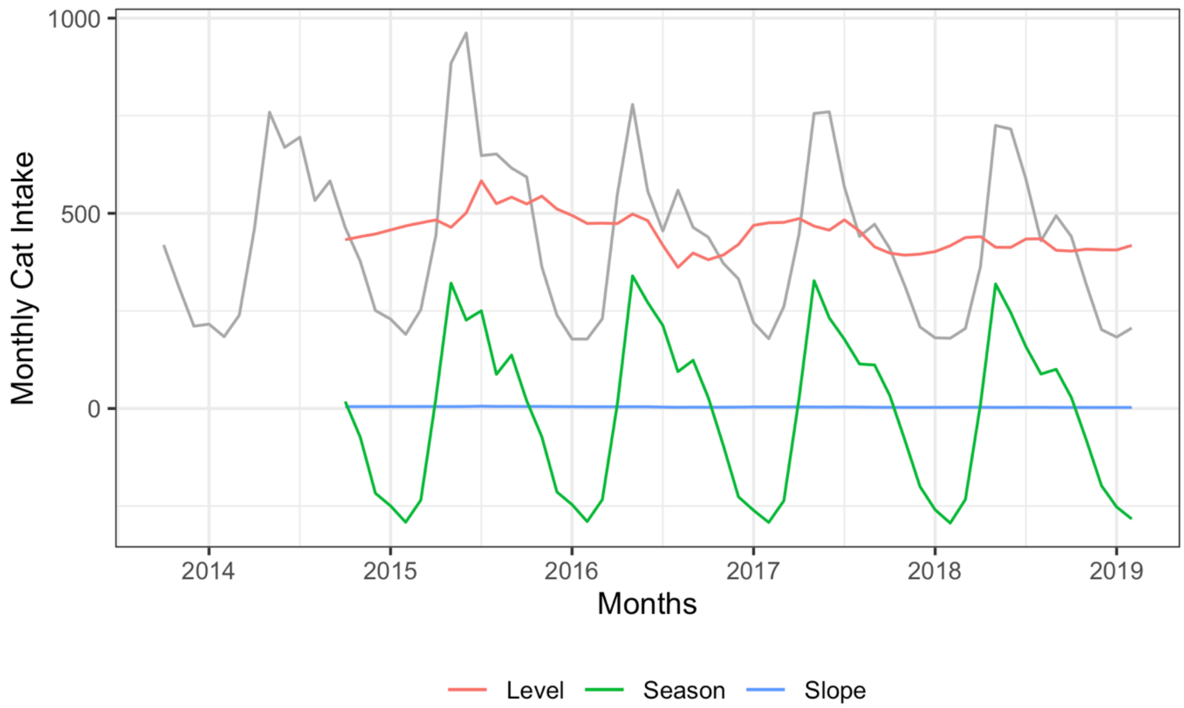

Figure 8 - Smoothed Components for Cat Intake

The gray line is the 65 months of training data for the cat intake time series.

The red line is the smoothed Level component. This is smoothing (or a weighted moving average of) the seasonally adjusted data (original time series minus the seasonal component). The smoothing parameter (alpha = 0.337) is interpreted as approximately the prior observation is given a weight of about 1/3. The remaining 2/3 of the weight is applied to the prior smoothed values of the series. The alpha smoothing parameter is on the lower end of the scale, so the smoothed Level component represents the medium to long-term trend of the time series' seasonally adjusted data.

The blue line is the smoothed Slope component. The beta smoothing parameter is almost zero (0.009), so there is no perceptible upward or downward trend, and the slope has little impact.

The green line is the Season component (centered on zero). It is a weighted moving average of the seasonal component of the time series. The smoothing parameter (gamma = 0.296) indicates the prior season will have a weight of about 30%, and the remaining 70% of the weight exponentially declines over all the earlier seasons. With a lower value, the seasonally smoothed component slowly incorporates changes of the most recent season.

Figure 9 illustrates how the smoothed components (level, slope & season) are combined to produce the Holt-Winters model's fitted value. The fitted value (thick red line) is simply the sum of the components. As mentioned above, there is no perceptible change in the Slope component. The Level component is essentially pushing up or pulling down the Seasonally smoothed component.

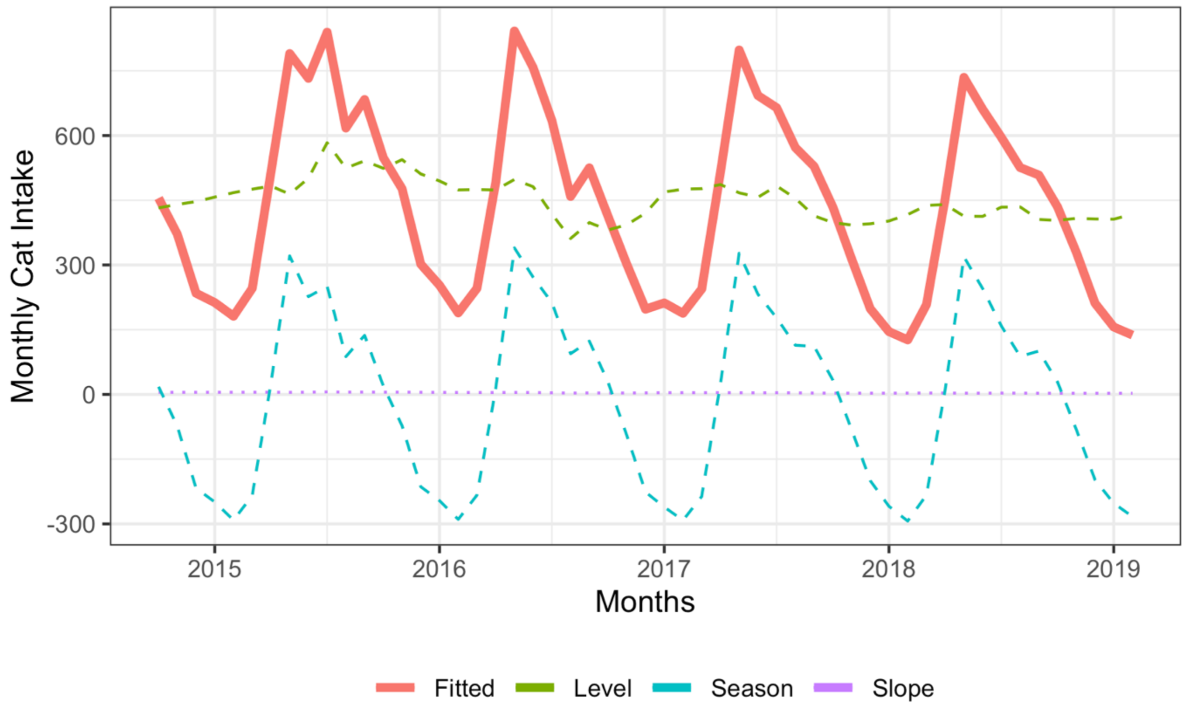

Figure 9 – Fitted Value from the Smoothed Component for Cat Intake

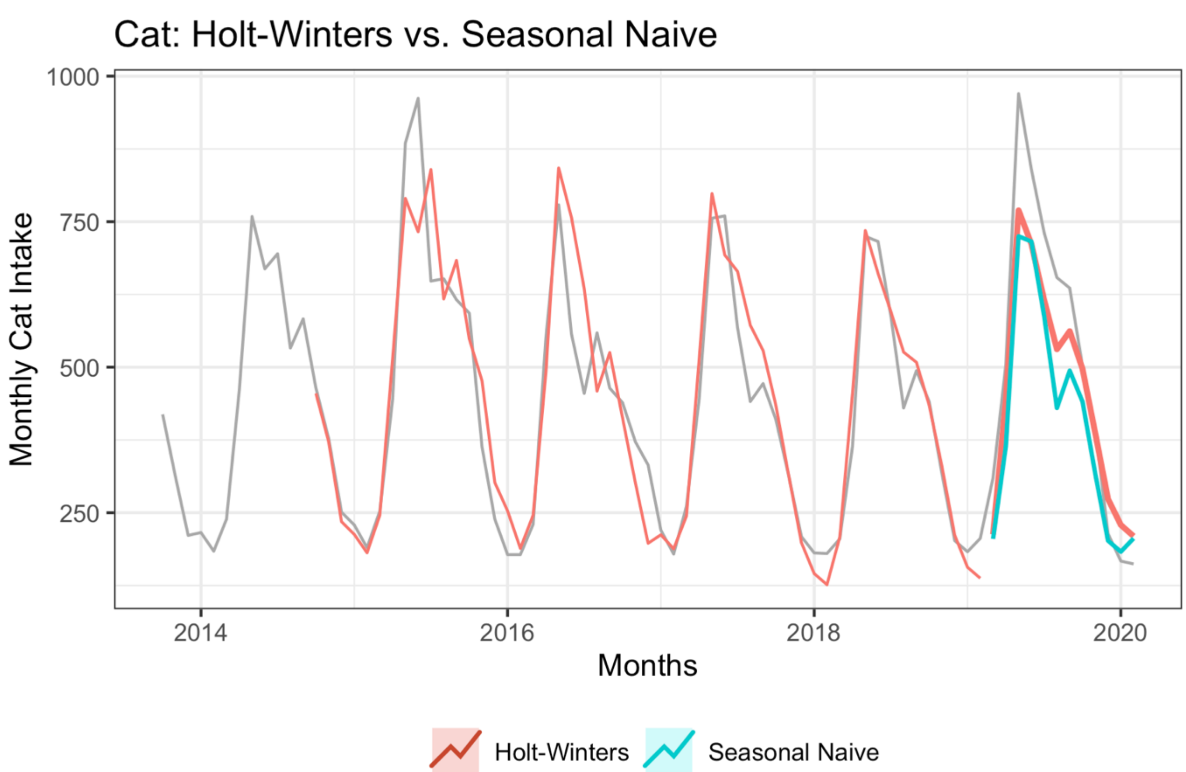

Figure 10 - Holt-Winters compared to Seasonal Naive Forecast

Figure 10 shows the fitted values from the Holt-Winters model and compares its forecast with the Seasonal Naïve benchmark. Again, the gray line is the cat intake time series, the thin red line on the left side represents the fitted values from the Holt-Winters exponential smoothing model. The thicker red line on the right-hand side is the forecasted values for the test set or the next 12-month period in the future. For comparison, the light blue line is the Seasonal Naïve forecast, which is identical to the values in the prior 12-month period (on the gray line).

Recommendation

Both the Regression on Seasonality and Holt-Winters models have about 27% less error than the Seasonal Naïve approach. Digging into how both models work, I believe the Regression on Seasonality is the better approach for cat intake.

Seasonality is the primary force in the cat intake time series. Regression resulted in a single fixed definition of the seasonal cycle, which minimized the error across the five seasonal cycles in the available training data. And that cycle appears stable – does not shift a lot year to year. This leads more to conclude that regression will result in a more reliable forecast for cat intake.

As more data is collected, it may be worthwhile for the forecast to adjust to changes in the trend and seasonal cycle, which is possible with a smoothing model. But in this case, adjustments in the trend and seasonality pull the model/forecast down and in the wrong direction.

Discussion of Models for Dog Intake

The **Seasonal Naïve** time series forecasting method for dog intake results in an error on average of about 78 dogs per month. Referring back to the descriptive statistics, the time series forecast is less accurate than just using the monthly average of 603 dogs with a standard deviation of +/- 56 dogs per month.

Regression on Seasonality

For dog intake, I also started with a regression model with only seasonal predictors. The Adjusted R^2 is 0.20, indicating that the seasonal component explains only a mere 20% of the variation in the data. Applying the model to the test data set and forecasting the next 12 months results in a RMSE of 41.1. On average, the forecast may be off by about 41 dogs per month, which is 48% better than the benchmark.

Table 5 presents the coefficients and forecast of dog intake for this regression model using January as the reference month. With dog intake, the seasonal predictors are not as statistically significant as we saw with the cat intake model.

Figure 11 plots the dog intake time series (gray dashed line) as well as the fitted values (lighter red line) of the seasonal regression model in addition to the regression model's forecast (thicker dark red line on the right) and the benchmark Seasonal Naïve forecast (light blue line).

On dog intake, the fitted values do not mirror the original time series quite as well as we saw with cat intake. In the first few years, the fitted values fall below the actual time series and above in the later years. The seasonal estimates are the same fixed values across each year and carried forward to forecast the final year of data. Notice with the Season Naïve forecast (light blue line) that, in this case, the prior year is not a good estimate for how dog intake will unfold in the following year. The Seasonal

Naïve forecast is quite different from the test set (solid gray line). That helps explain why there is a big difference in the error (RMSE) between the two approaches.

Table 5 - Coefficients & Forecast for Dog Regression on Season

Variable	Estimate	Std. Error	t value	Pr(> |t|)	Signif.
(Intercept)	612.67	20.68	29.63	< 2e-16	***
Feb	-78.67	29.24	-2.69	0.010	**
Mar	-5.07	30.67	-0.17	0.869	
Apr	-37.27	30.67	-1.22	0.230	
May	60.13	30.67	1.96	0.055	.
Jun	4.33	30.67	0.14	0.888	
Jul	-0.47	30.67	-0.02	0.988	
Aug	-34.27	30.67	-1.12	0.269	
Sep	-28.27	30.67	-0.92	0.361	
Oct	15.17	29.24	0.52	0.606	
Nov	-11.00	29.24	-0.38	0.708	
Dec	-34.00	29.24	-1.16	0.250	

Forecast	
Month	Dog Intake
Jan	613
Feb	534
Mar	608
Apr	575
May	673
Jun	617
Jul	612
Aug	578
Sep	584
Oct	628
Nov	602
Dec	579

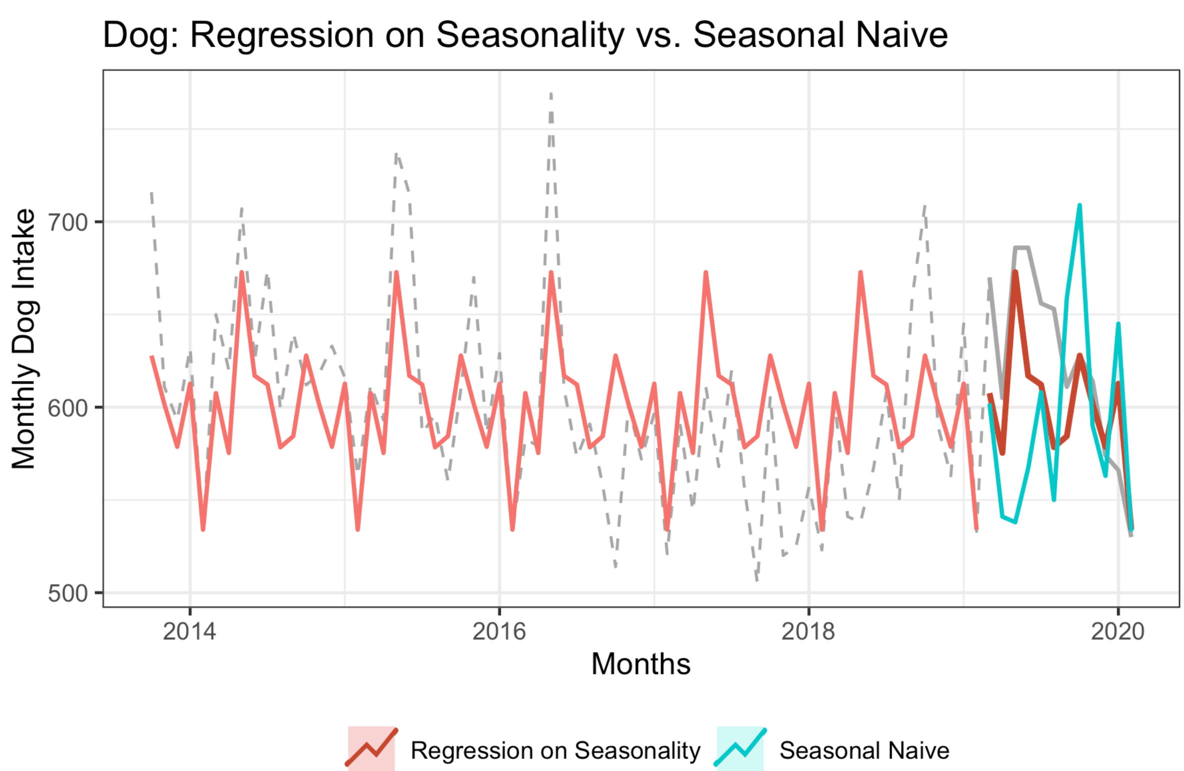

Figure 11 - Regression on Seasonality compared to Seasonal Naïve Forecast

Other Regression Variations

As with the cat intake models, I also experimented with adding trend predictors. Adding a linear trend improved the Adjusted R^2 from 0.20 to 0.34, but accuracy suffered (RMSE increases from 41.1 to 71).

Adding a quadratic trend (i.e., Trend + $Trend^2$) produced better results. The Adjusted R^2 improved from 0.20 to 0.37, and accuracy was only slightly worse (RMSE increases from 41.1 to 44.7). However, the trend terms were only marginally significant, so this did not appear to be a great path to pursue.

Holt-Winters Exponential Smoothing

The Holt-Winters model for dog intake resulted in the smoothing parameters presented in Table 6.

Table 6 - Smoothing Parameters for Dog Intake

Component	Parameter	Value
Level	alpha	0.154
Slope	beta	0.000
Season	gamma	0.082

Figure 12 displays the Level, Slope, and Season components for the dog intake training data after being smoothed by the given parameters. For reference, the gray line is the training data of the time series.

The red line is the Level component, which is smoothing the seasonally adjusted data. The smoothing parameter (alpha = 0.154) is interpreted as the prior observation is given a weight of approximately 15%. The remaining 85% of the weight is applied to the seasonally adjusted data's prior smoothed values. This value is on the low end of the scale, and the smoothed Level component represents the long-term trend of the seasonally adjusted data rather than more rapidly incorporating short-term ups and downs.

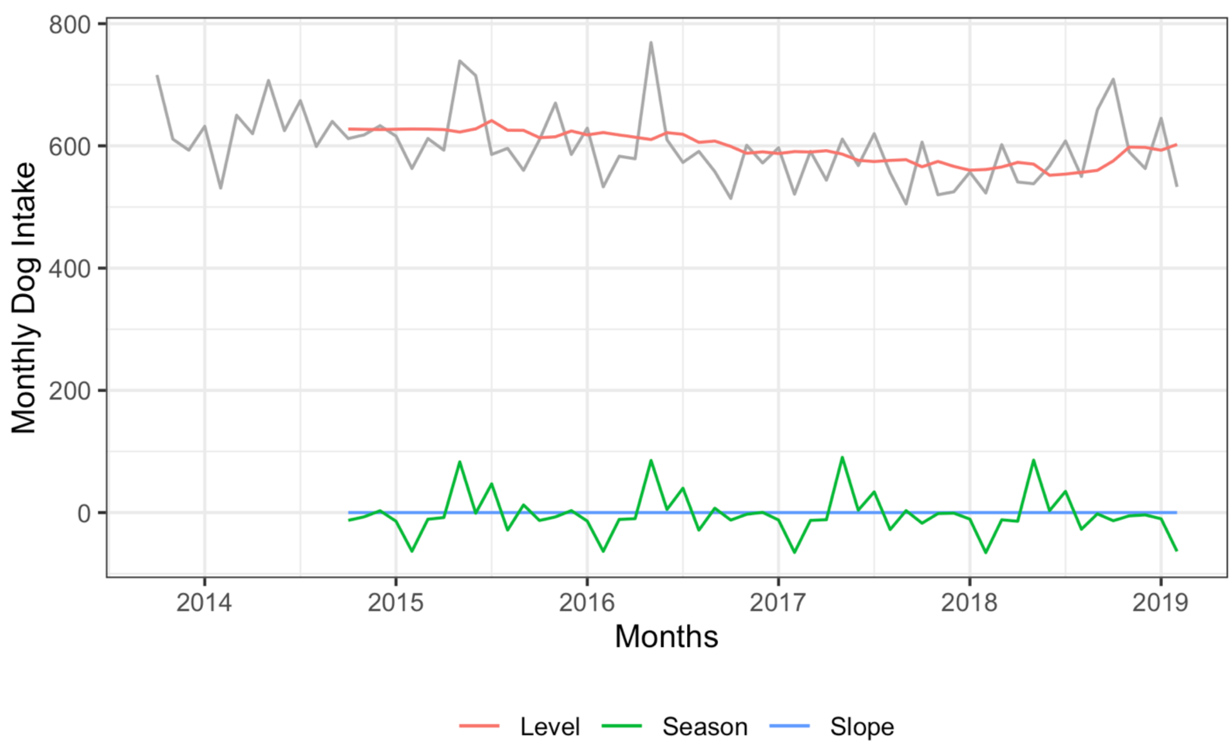

Figure 12 - Smoothed Components for Dog Intake

The blue line is the smoothed Slope component. The beta smoothing parameter is zero in this case, so there is NO upward or downward trajectory in the data, and the slope has no impact.

The green line is the Season component (centered on zero). The smoothing parameter (gamma = 0.082) indicates the prior season is given a weight of about 8%. The remaining 92% of the weighted average comes from the prior seasons. With a small parameter value, the seasonally smoothed component slowly incorporates recent changes to the time series' seasonal cycle. In this case, the seasonal component is nearly constant but shrinks or narrows very slightly in the later years, reflecting a long-term trend.

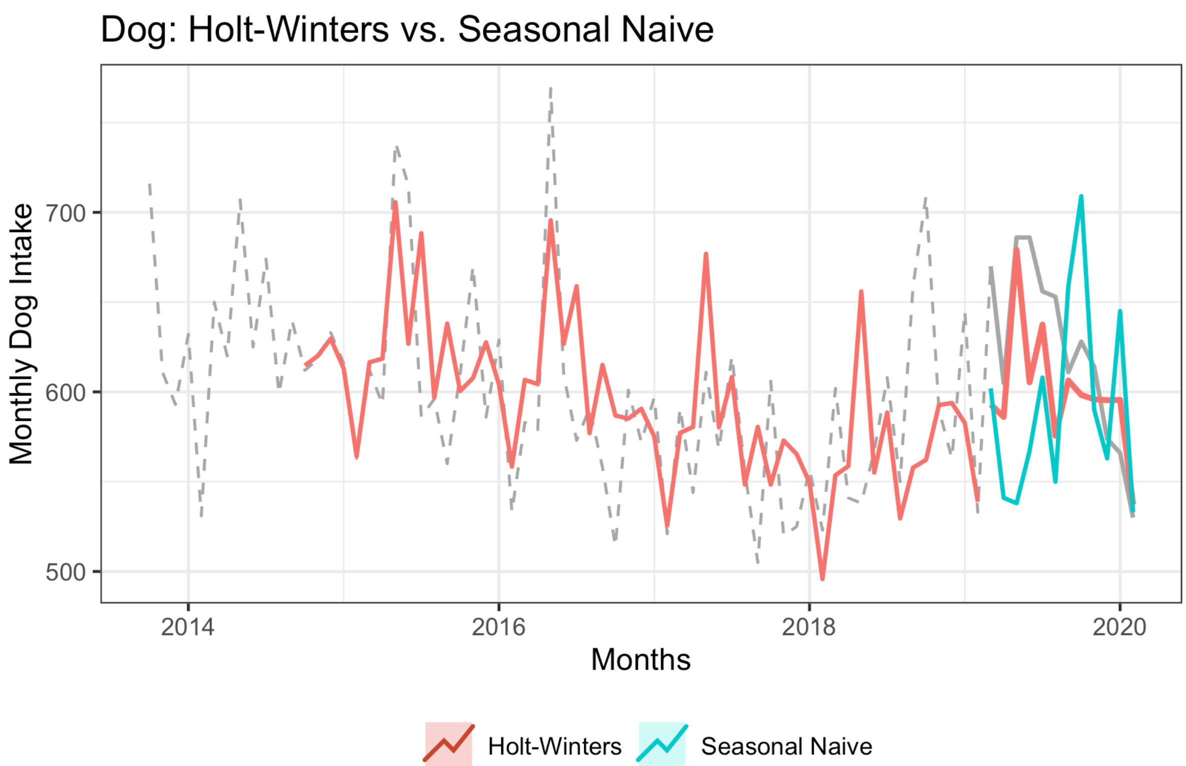

Figure 13 - Holt-Winters compared to Seasonal Naive Forecast

Figure 13 shows the fitted values from the Holt-Winters model and compares its forecast with the Seasonal Naïve benchmark.

The gray dashed line is the dog intake time series, the thin red line on the left side is the fitted values used to train the Holt-Winters exponential smoothing model. The thicker red line on the right-hand side is the forecasted values for the next 12-month period in the future. For comparison, the light blue line is the Seasonal Naïve forecast, which is identical to the values in the prior 12-month period (gray dashed line).

The fitted values (thinner red line) stay relatively close to the dog intake time series (gray dashed line). The smoothed level component pulls down the season component across the dip in 2017 and 2018. And the forecast for the last 12 months is close to the actual dog intake in that period (solid gray line). Again, it is clear the prior 12 months (light blue line) of the Seasonal Naïve forecast is just not a good proxy for what will happen in the following 12 months in this case.

Recommendation
The Regression on Seasonality and Holt-Winters models outperform the Seasonal Naïve benchmark, in this case, by about 46% (an error of about 42 dogs per month versus 78). In this case, I believe the Holt-Winters smoothing model is more appropriate for dog intake.

Regression produces a constant or fixed model of the number of dogs entering the shelter per month as the only factor involved in the model/forecast. Seasonality drives some of the fluctuation in dog intake, but seasonality is not the only or necessarily the overwhelming factor.

The Holt-Winters smoothing approach, which incorporated both the level and seasonality factors and can adjust to trends in the data over time, is a more robust model for dog intake characteristics.

Results of Analysis
The project demonstrated that several relatively straightforward time series forecasting techniques are meaningful improvements (27-65%) over simply projecting forward the prior year's results. Animal intake is the fundamental demand that drives the operation of animal shelters, and a more accurate estimate would improve a variety of budgeting and planning activities.

For example, a good forecast of future intake could help assess the impact of different interventions. The city of Austin is quite innovative in animal welfare. They look at data and design and adjust programs to attempt to improve results. A reliable forecast of intake could be the baseline to measure if a new program or intervention (e.g., more targeted spay/neuter, support for community cat caretakers, educational programs) had a meaningful impact on animal intake.

COVID hit the animal sheltering world at a particularly inopportune time – the start of kitten season. There was much angst about curtailing intake and not spaying/neutering the latest crop of kittens. The forecast for intake gives us some idea of the number of missed kittens out in the community. It will be interesting to understand the impact of foregoing typical intake. Will we be overrun with cats next year? Does the population naturally stabilize in the wild and some of our interventions may turn out to be unnecessary? Do communities re-double efforts in the typically slow fall and winter months to round up cats missed this spring and do large-scale spay/neuter events as restriction ease up? These are interesting times in which we live!

Conclusion
One thing I find rewarding about data analysis projects is that you start with a data set you know very little, if anything, about, and by the end, you come away with a real command of what the data is telling you.

Other than some awareness of "kitten season," I did not have any idea about the ebbs and flows of animal intake. I learned that kitten season was very pronounced in the data, but seasonality was much less discernable in dog intake.

It was interesting to decompose the time series into its fundamental elements – level, trend-cycle, and seasonality and produce reasonably good results with just those pieces – no other predictors. Understanding the time series components helped me dig into the models and understand how they worked and produced a forecast, which informed my view of which model was best for each time series.

I am also glad I analyzed two time series with different characteristics (intake of cats versus dogs). Sometimes a pattern was evident in one, but things felt like a cluttered mess with the other time series. But when I had an "aha moment" around what a model was doing with one series, then it was easier to see how the concept applied to the other series as well.

I look forward to incorporating additional predictors to do more analysis with cross-sectional data or venturing into more involved time series analysis techniques such as ARIMA models.