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Top Line

NOTE: This analysis is built from a time series forecast and is not certified by accounting. It is only meant to help visualize trends.

We built a forecast model to set a useful baseline for the business to build from. The business owner for this metric will ultimately set where were they want the business goal to land.

4 different forecasting models were applied, and are displayed below. These different models allow us to understand the potential impact of different scenarios.

- Model 1 (High): Covid data included, and covid period counted as 3/1/2020 5/1/2021
 - This model produces the smallest forecasted traffic, due to the impact of the negative trend.
- Model 2 (Low): Covid data included, leveled negative growth trend
 - This model producess a forecasted traffic that is close to 2021 traffic.
- Model 3 (Mid): Covid data not included (then forecast 3 years out)
 - This model essentially is built with the belief that the trends pre-2020 will continue. Ultimately the business question here is whether shopper behavior will fully return to pre-pandemic behaviors in 2022.

	2017	2018	2019	2020	2021	2022FC_High	2022FC_Low	2022FC_Mid	Business Goal
Jan	\$200.1M	\$213.9M	\$201.0M	\$214.3M	\$211.5M	\$263.8M	\$222.1M	\$234.7M	TBD
Feb	\$253.3M	\$262.3M	\$249.0M	\$257.6M	\$210.7M	\$301.1M	\$259.8M	\$284.4M	TBD
Mar	\$347.3M	\$398.3M	\$389.6M	\$164.9M	\$452.0M	\$439.0M	\$393.1M	\$409.4M	TBD
Apr	\$363.0M	\$328.5M	\$361.1M	\$2.1M	\$379.3M	\$385.3M	\$339.1M	\$373.2M	TBD
May	\$349.1M	\$381.9M	\$372.1M	\$91.8M	\$401.7M	\$406.4M	\$359.7M	\$393.6M	TBD
Jun	\$411.8M	\$433.5M	\$433.0M	\$331.5M	\$476.2M	\$460.3M	\$417.1M	\$453.3M	TBD
Jul	\$439.2M	\$460.3M	\$451.0M	\$363.8M	\$494.1M	\$486.2M	\$442.8M	\$477.0M	TBD
Aug	\$450.6M	\$475.4M	\$485.6M	\$380.4M	\$480.4M	\$509.4M	\$466.3M	\$497.9M	TBD
Sep	\$377.9M	\$360.1M	\$357.5M	\$377.8M	\$394.9M	\$409.0M	\$366.1M	\$390.7M	TBD
Oct	\$327.4M	\$339.2M	\$350.7M	\$325.3M	\$377.3M	\$392.6M	\$350.2M	\$366.5M	TBD
Nov	\$494.4M	\$509.8M	\$513.8M	\$421.4M	\$532.2M	\$557.7M	\$515.9M	\$531.6M	TBD
Dec	\$574.8M	\$576.3M	\$595.5M	\$541.4M	\$629.8M	\$637.9M	\$596.6M	\$608.5M	TBD
total	\$4.59B	\$4.74B	\$4.76B	\$3.47B	\$5.04B	\$5.25B	\$4.73B	\$5.02B	_

Reviewing Historical Data

Overview of Data

Data Generation

Sales data is reported monthly by some of the retailers at the centers.

Data Pull from DB

For forecasting purposes we have pulled data for all centers from 2016 until now (2022.01.26).

Source: OpsStats (server: WAREHOUSESQL)

Tables: [Warehouse].[dbo].[FactAdjustedSales]

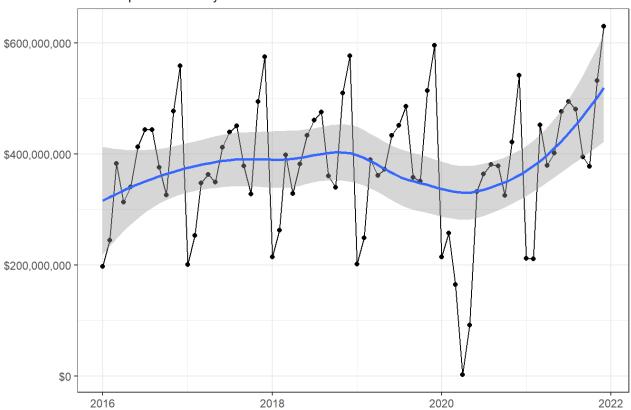
- There are some retailers who are only required to report once a year (TJ Max?)
- The results are not controlled/adjusted by the count of retailers reporting
- Only currently active centers are included in what is analyzed below.

View of Trends

Before we begin to model this work, we want to visualize the general trends. This allows us to to flag for large outliers or anomalies within our data.

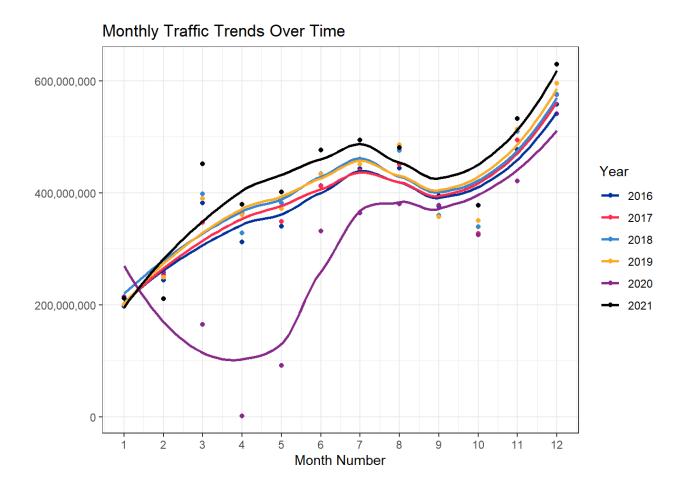
- With this data we can see how significant Covid shutdowns had on traffic throughout 2020.
- We also see a fairly consistent month to month seasonal variation.

Monthly Retailer Revenue Trends Over Time Sales reported monthly



Monthly View

Each color line represents a different year's worth of traffic aggregated on a monthly basis.



Forcasting model

Why Synthetic Controls?

This method can account for the effects of confounders changing over time, by weighting the control group to better match the treatment group before the intervention. Another advantage of the synthetic control method is that it allows researchers to systematically select comparison groups. It has been applied to the fields of political science, health policy, criminology, and economics.

In our case, we are using this methodology to help set a baseline of where the business would be if we continue with the same historical processes and procedures as before.

Step 1: Build Forecast Model

Building model for all entire portfolio.

- In this case, we are already into 2022, but we want to build the forecast model excluding the new year.
- In the future data frame, we go forwards 365 days (1 year) to be able to predict against.

```
Sales <-
   CleanSales %>%
   filter(Date < as.Date("2022-01-01")) %>%
   mutate(ds = Date) %>%
   group_by(ds) %>%
   summarise(y = sum(sales, na.rm=T)) %>%
   ungroup()

# m <- prophet(Traffc, holidays = covid)
m <- prophet(holidays = covid)
m <- add_country_holidays(m, country_name = 'US')
m <- fit.prophet(m, Sales)

future <- make_future_dataframe(m1, periods = 24, freq = 'month')
# tail(future)

forecast <- predict(m, future)
# tail(forecast[c('ds', 'yhat', 'yhat_lower', 'yhat_upper')])</pre>
```

Forecast Results

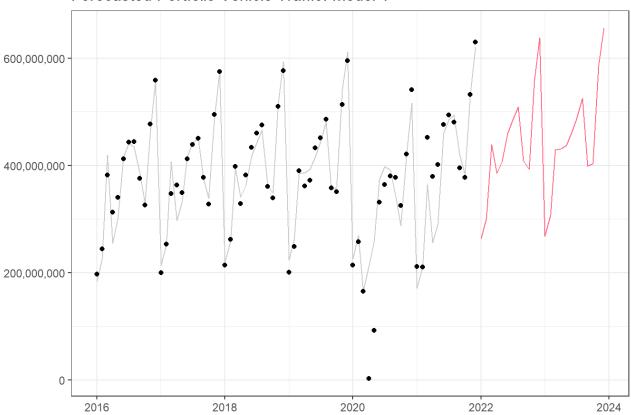
Below is the forecast model.

- The black dots represent to the total portfolio traffic by day.
- The blue line represents the forecasted values.

We see a strong degree of seasonality

Forecast Model 1

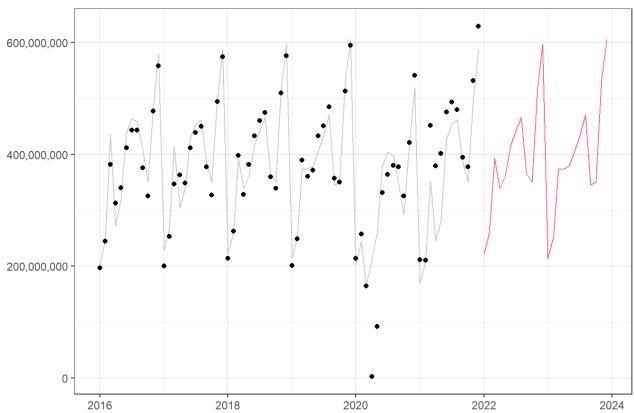
Forecasted Portfolio Vehicle Traffic: Model 1



Red Line: Forecasted Vaules | Blue points: Actual Traffic during holdout period

Forecast Model 2

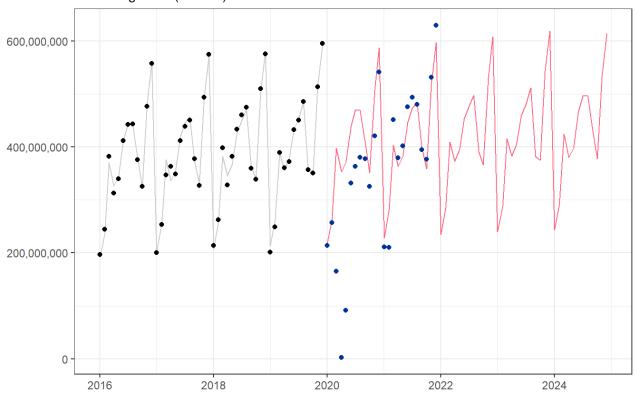
Forecasted Portfolio Vehicle Traffic: Model 2



Red Line: Forecasted Vaules | Blue points: Actual Traffic during holdout period

Forecast Model 3

Forecasted Portfolio Vehicle Traffic: Model 3 Removing 2020 (COVID) onwards from forecast model



Red Line: Forecasted Vaules | Blue points: Actual Traffic during holdout period

Forecast Components

A forecast model can be broken up into the different elements that add (or multiply) together. By splitting them out and visualizing them, we then can view the index values and assess the impact of different items on the results

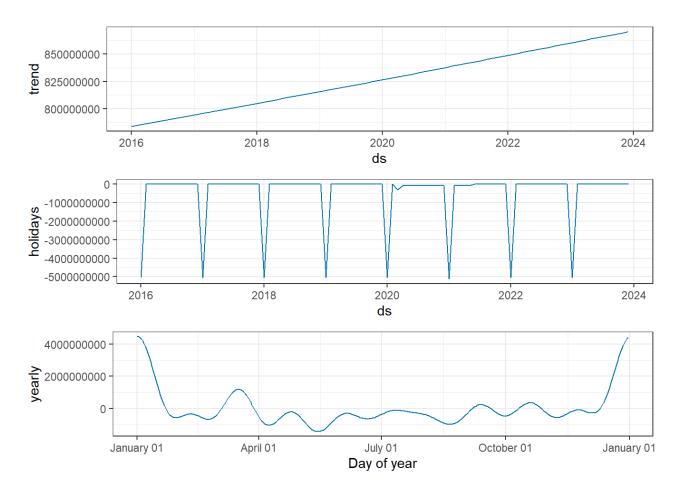
By breaking down the forecast into it's component parts we see a couple of things:

- Trend: This element shows what the general trend is year over year.
 - In this case, there is a forecasted to be a downwards trend for future years.
- Holidays: This elements flags both the US holidays as well as the date range from 3/1/2020 5/1/2021 as the main effect of Covid shutdowns.
- Weekly: This element shows how traffic varies within the week.
 - The outlets being a mainly weekend business really shows up in this view, with the positive indices being for Friday, Saturday, Sunday.
- Yearly: This is the element of the within year seasonality.
 - In general we see that there is a general ramp up throughout the first part of the year, a small lull in October, and then our biggest traffic volumes seen during the end of year.

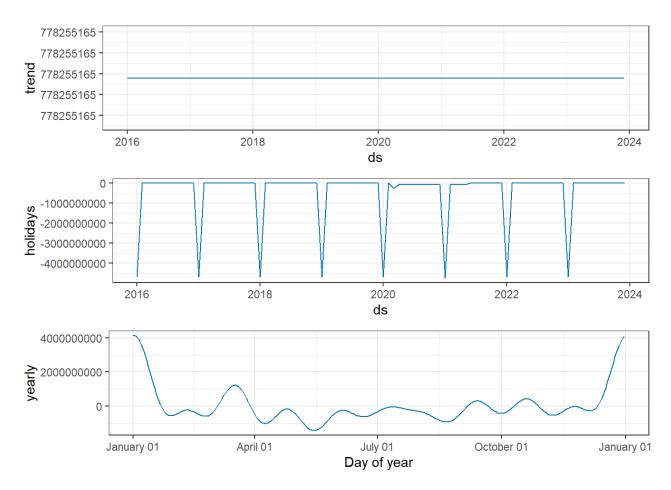
Note about negative values: These 4 items below are added together to create the forecast model. This is why there are some items that are negative and some that are positive. A negative value does not mean that we would forecast negative vehicles, but instead that at those instances the traffic would decrease from the trend.

• An example here would be the impact of Christmas day on traffic. As many centers are closed on that day, we see in the holiday component that there is a large negative value.

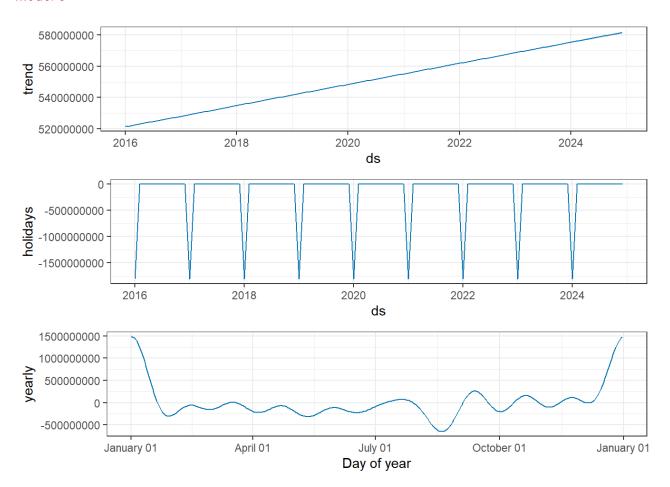
Model 1



Model 2



Model 3



Next Steps

The "Top Line" section presented both the actuals traffic by month for prior years with the forecasted values for 2022 (bolded).

The forecasted values could represent what would be considered as the baseline for goal setting by the business. Upon which the business leaders responsible for this metric would review and adjust the values according to where they believe they can made an impact. It will be up to the business to determine what strategies they will implement and adjust the goals accordingly.

This analysis body of work is set up to allow for the adjustment of goals based upon the values decided upon by the business owners.

Appendix

SQL: Traffic

```
select dimd.fulldate, dimc.CENTERNAME, dimc.BldgGroupName, dimc.[BLDGID],
        dimt.TangerCatDesc, dimt.TangerSubCatDesc, diml.TenantName,
        diml.ChainName, diml.leasid
,dime.PORTID,fas.ISTEMP, fas.IsCurrentlyOpen,fas.ISNONREPORTING,
        fas.IsOpenForFullYear, diml.zPopUpProgram, lastlsf,
        [CurrentYearSales1M],
cast(iif(lastlsf = 0 or lastlsf is null, 0, [CurrentYearSales1M]/lastlsf) as
        money) as AdjustSPSF
from warehouse.dbo.FactAdjustedSales fas
    left join warehouse.dbo.DimLease diml on fas.LeaseKey = diml.LeaseKey
    left join warehouse.dbo.DimCenter dimc on fas.CenterKey = dimc.CenterKey
    left join warehouse.dbo.DimTenant dimt on fas.TenantKey = dimt.TenantKey
    left join warehouse.dbo.DimEntity dime on fas.EntityKey = dime.EntityKey
    left join warehouse.dbo.DimDate dimd on fas.dateKey = dimd.DateKey
where fas.DateKey > 20151231
--and last1sf > 0
order by CENTERNAME, fas.datekey desc, tenantname
```

Forecast Model

The forecast model code is available within the I&A OneDrive.