US Passenger Airline Post-Pandemic Recovery

A Time Series Analysis

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Section 1

Background

Concept: to analyze historical data from 2015-2020 in order to understand passenger trends in commercial aviation.

The COVID-19 pandemic brought leisure and business air travel to a near-screeching halt in the second quarter of calendar year 2020.

Experts propose that a full recovery could take upwards of 2.5 years.

In this research, I aim to provide insight on the forecast for recovery amongst three leading US airline carriers in the post-COVID-19 environment:

1. United Airlines (UA)
2. Delta Airlines (DL)
3. American Airlines (AA)

Data is open source and provided by the US Bureau of Transportation Statistics (BTS).

Metrics

Revenue Passenger Miles (RPM), a key indicator of an airline's operational load, can be modeled as a time series.

$$RevenuePassengerMiles(RPM) =$$

$$NumberofPayingPassengers * DistanceTraveled$$

Subsection 1

The Problem Statement

Problem

How should we expect the largest US passenger airlines to operate in the aftermath of COVID-19?

This particular question is important because it seeks to provide predictive insight to how the US airline giants will be expected to operate if the travel demand resumes in 2021 or 2022.

If they can predict this, the airlines should be able to strategically ramp up and meet the demand.

If they do not forecast appropriately, they may fail, and the second- and third-order effects will be global.

My model will use recent historical data to identify Revenue Passenger Mile trends right up to the COVID-19 onset, and then forecast the expected output (RPM) of UA, DL, and AA if normal travel resumes.

Section 2

The Data

The Data

Data for this research is downloaded from the BTS website:

-https://www.transtats.bts.gov/DL_SelectFields.asp?gnoyr_VQ=FIM

-Analysis is specific to *"domestic segments"*; flights that terminated in the US or its territories.

-Metrics aggregated at a **monthly** frequency.

-The time period of interest was **January 2015 to November 2020**.

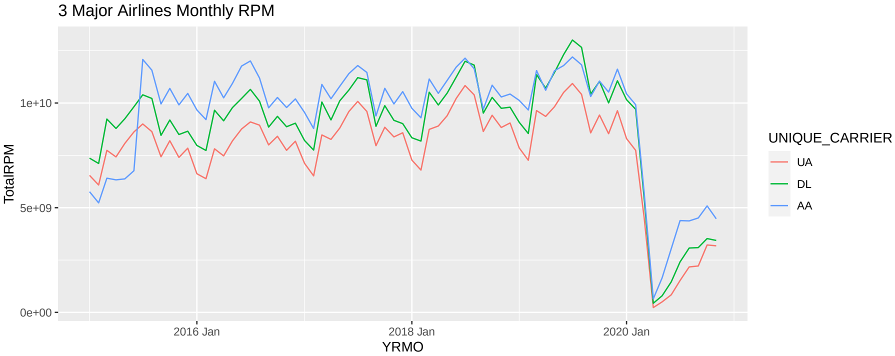
-This produced **71 monthly observations** for each of the "Big 3" airlines, which is a total of 213 data points for each metric.

A monthly interpretation of historical travel data appropriately highlights the seasonal trends of the year without being too granular.

Historical Data Exploration

2015-2020: Effects of COVID-19

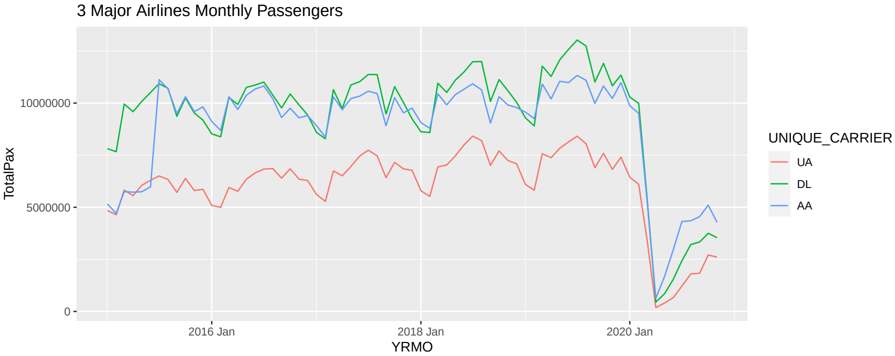
Monthly RPM



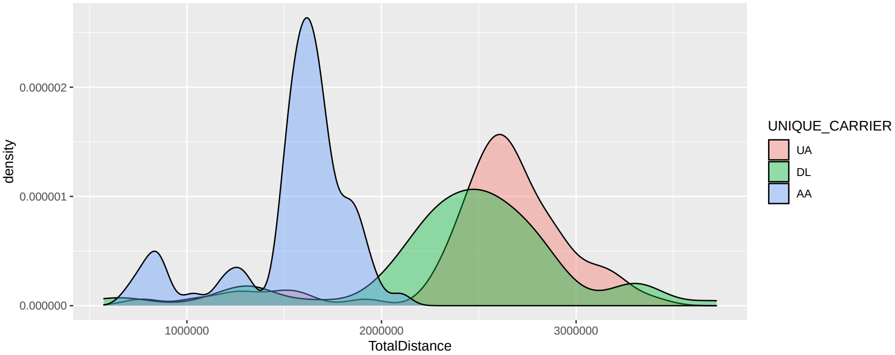
Historical Data Exploration

2015-2020: Effects of COVID-19

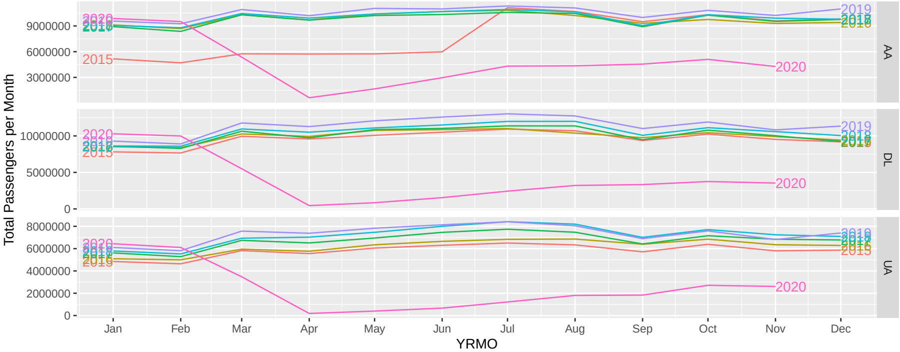
Monthly Passengers



Revealing each airline's strategy

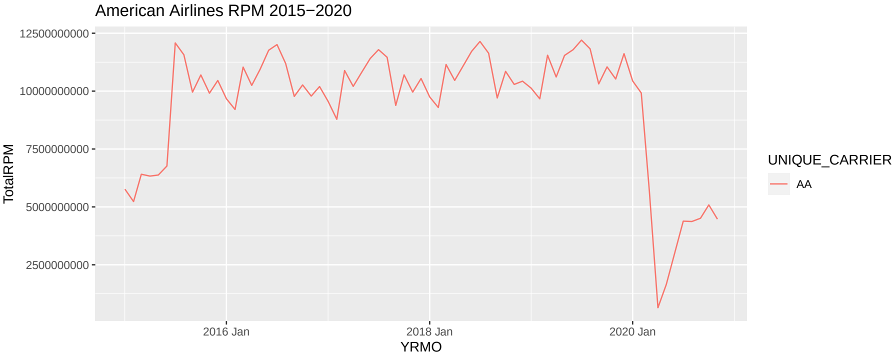


Seasonal Plots



2015 - A Weird Year for American Airlines

There was an interesting phenomenon for American Airlines in summer 2015, where their Total Passenger count increased greatly.



After some research into the cause of this spike, I decided to remove 2015 observations from the American Airlines data set.

Model Assumptions & Limitations

1. Assume that the "Big 3" airlines can show trends that are representative of the entire US passenger airline industry
2. Assume that RPM is indeed the proper metric to measure operational capacity of a particular carrier
3. Assume that data from 2015 - 2019 is sufficient for modeling (48 monthly observations)
4. **Assume that changes in external forces do not hold a significant bearing on RPM**

- Strategic corporate decisions
- Passenger preferences

Section 3

Forecast Model for Airline Recovery

Subsection 1

Choosing a Model

ARIMA

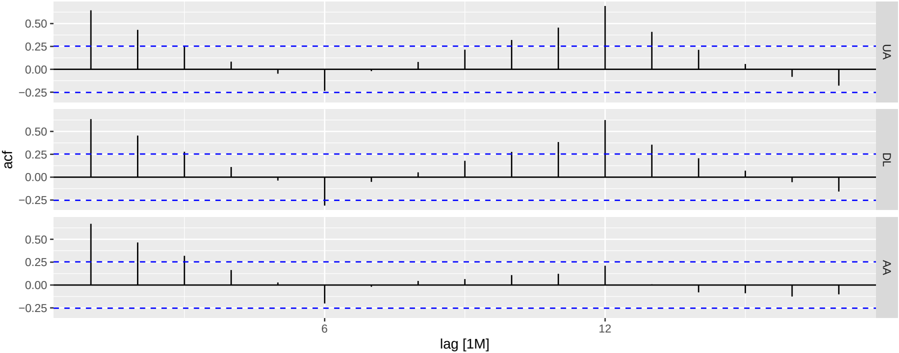
-Revenue Passenger Miles over time is modeled using an Autoregressive Integrated Moving Average (ARIMA model) with seasonal and non-seasonal components.

-***Each airline gets its own model***

-To generate models, only include observed RPM through December 2019, *prior to any effects from COVID-19*

Modeling procedure borrowed from *Forecasting Principles and Practice, 3rd edition.*

Autocorrelation Features



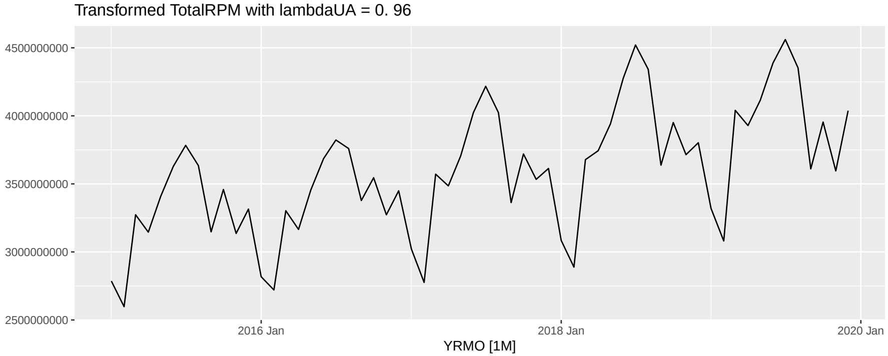
Box-Cox Transformation

Guerrero features search was used to find the optimal lambda values (to be used in Box Cox transformation).

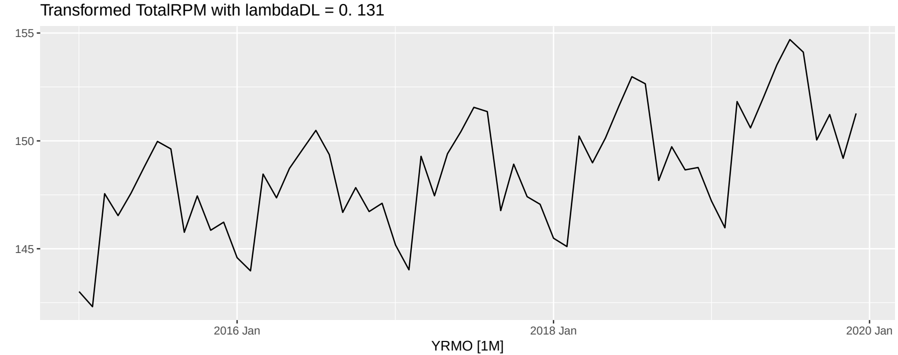
The goal is **to make the size of seasonal variation about the same across time series**.

Once we transform the data, we can look at the first-difference and second-difference to help determine which values to use for parameters (p,d,q) and (P,D,Q).

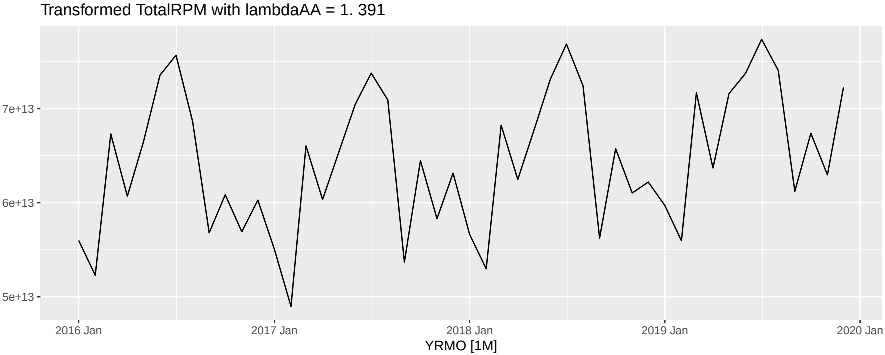
UA Transformed



DL Transformed



AA Transformed



Spectral Entropy

feat_spectral will compute the (Shannon) spectral entropy of a time series

- a measure of *noise* in our transformed data.
- A series which has strong trend and **seasonality**, entropy **close to 0**. (easier to forecast)
- A series that is very **noisy**, entropy **close to 1**. (difficult to forecast)

As seen below, the noisiest series is United Airlines, but they are all <0.55 and thus we continue modeling with this in mind.

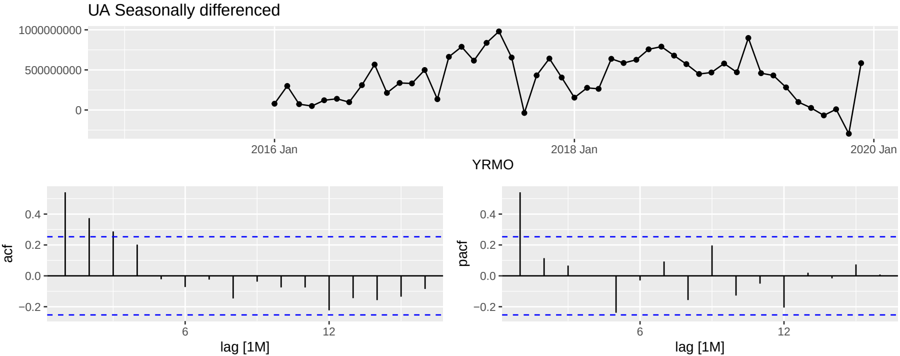
UA entropy	DL entropy	AA entropy
0.5330575	0.2167018	0.3617763

Stationarity

If the data are non-stationary, take first differences of the data until the data are stationary.

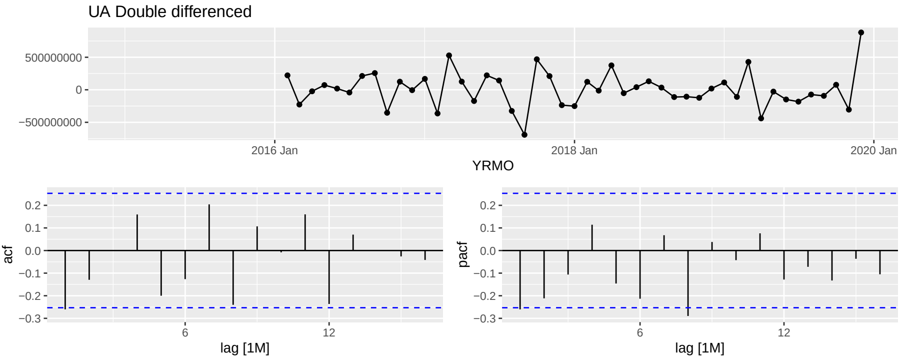
The data for all three airlines appears non-stationary, with an overall decline.

Below is a **United Airlines** Difference plot.



There is still clearly non-stationarity, so we take a further first difference.

UA difference plot (second difference)



Now we have a double-differenced ACF and PACF from which to generate our ARIMA model.

Repeat the process for the other 2 airlines to estimate ARIMA parameters.

Subsection 2

feasts::ARIMA()

feasts::ARIMA()

Using the *ARIMA* function in the *feasts* package, I generated three variations of ARIMA model for *each* airline:

1. ARIMA with user-defined parameters *p, d, q, P, D, Q* (based on visual assessment of ACF/PACF)
2. ARIMA with stepwise = FALSE, approx = FALSE for the full search
3. ARIMA with stepwise = TRUE for the quicker search

Feasts automatically generated the best models, by minimum AICc:

United Airlines model:

UNIQUE_CARRIER	.model	term	estimate	std.error	statistic	p.value
UA	UAauto	ar1	0.9481228	0.0440665	21.515718	0.0000000
UA	UAauto	ma1	-0.4742058	0.1718201	-2.759896	0.0081624
UA	UAstepwise	ar1	0.9481228	0.0440665	21.515718	0.0000000
UA	UAstepwise	ma1	-0.4742058	0.1718201	-2.759896	0.0081624

Delta Airlines model:

UNIQUE_CARRIER	.model	term	estimate	std.error	statistic	p.value
DL	DLauto	ma1	-0.7399767	0.1044291	-7.085924	0
DL	DLstepwise	ma1	-0.7399767	0.1044291	-7.085924	0

American Airlines model:

UNIQUE_CARRIER	.model	term	estimate	std.error	statistic	p.value
AA	AAauto	ar1	-0.8590480	0.1623904	-5.290019	0.0000067
AA	AAauto	ar2	-0.5542507	0.1698976	-3.262263	0.0024693
AA	AAauto	sar1	-0.6003123	0.1719776	-3.490643	0.0013227
AA	AAstepwise	ma1	-0.9288752	0.1348957	-6.885878	0.0000001
AA	AAstepwise	ma2	0.5099550	0.1817661	2.805557	0.0081473
AA	AAstepwise	sar1	-0.5128753	0.1899439	-2.700141	0.0106053

Best models formulated

The models that minimize estimated information loss (lowest AICc):

United: UAauto

fitUA Model formulation:

$$(1-\phi_1 B)\ (1-\Phi_1 B^{12})(1-B)(1-B^{12})y_t = (1+\theta_1 B)\ (1+\Theta_1 B^{12})\varepsilon_t$$

and the optimal parameters:

[AR(1) component] $\phi = 0.9481228$

[MA(1) component] $\Theta = -0.4742058$

Delta: DLauto

fitDL Model formulation:

$$(1-\phi_1 B)\ (1-\Phi_1 B^{12})(1-B)(1-B^{12})y_t = (1+\theta_1 B)\ (1+\Theta_1 B^{12})\varepsilon_t$$

and the optimal parameters:

[MA(1) component] $\Theta = -0.7399767$

American: AAauto

fitAA Model formulation:

$$(1-\phi_1 B)\ (1-\Phi_1 B^{12})(1-B)(1-B^{12})y_t = (1+\theta_1 B)\ (1+\Theta_1 B^{12})\varepsilon_t$$

and the optimal parameters:

[AR(1) component] $\phi 1 = -0.8590480$

[AR(2) component] $\phi_2 = -0.5542507$

[seasonal AR(1) component] $\Phi_1 = -0.6003123$

Subsection 3

Checking Residuals: **United**

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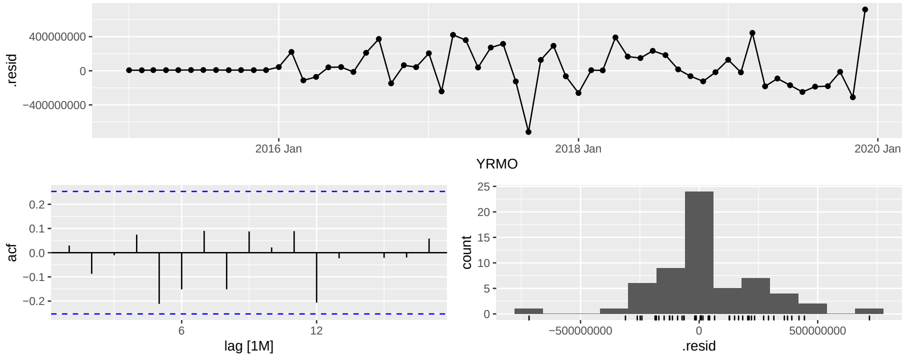

Subsection 4

Checking Residuals: **Delta**

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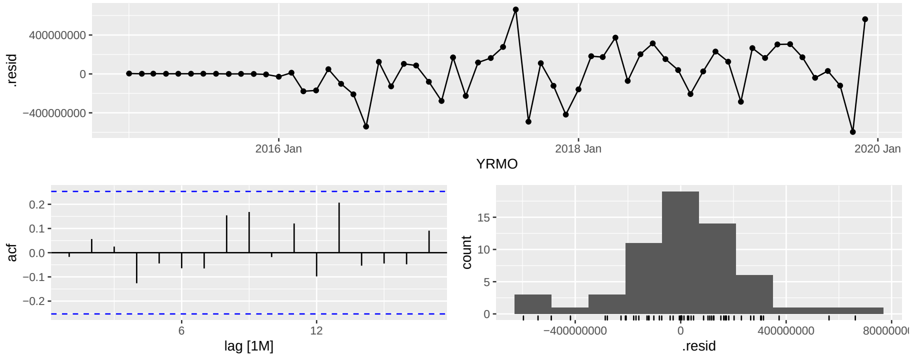

Subsection 5

Checking Residuals: **American**

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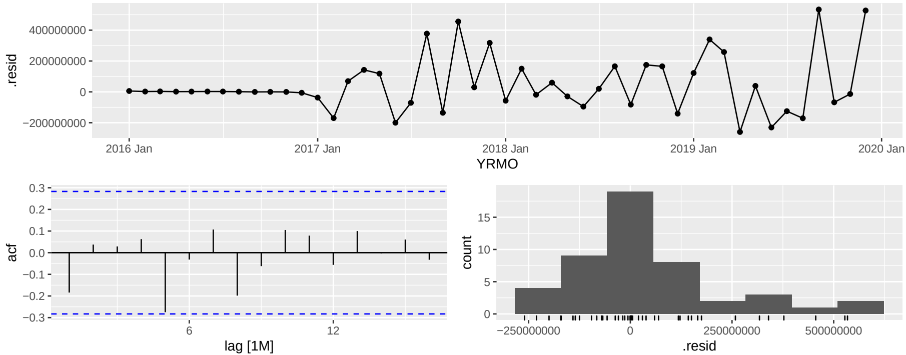

Ljung-Box test

Use a Ljung-Box test to confirm that the residuals are consistent with white noise.

The large p-values shown below indicate that our seasonal ARIMA models have all passed the checks and are ready for forecasting.

UNIQUE_CARRIER	.model	lb_stat	lb_pvalue
UA	ARIMA110820	NA	NA
UA	UAauto	17.96349	0.5898136
UA	UAstepwise	17.96349	0.5898136

UNIQUE_CARRIER	.model	lb_stat	lb_pvalue
DL	ARIMA1220120	NA	NA
DL	DLauto	17.02371	0.6514338
DL	DLstepwise	17.02371	0.6514338

UNIQUE_CARRIER	.model	lb_stat	lb_pvalue
AA	AAauto	22.58476	0.3096405
AA	AAstepwise	23.72722	0.2545110
AA	ARIMA420520	NA	NA

Subsection 6

The Forecast: 2021 and beyond

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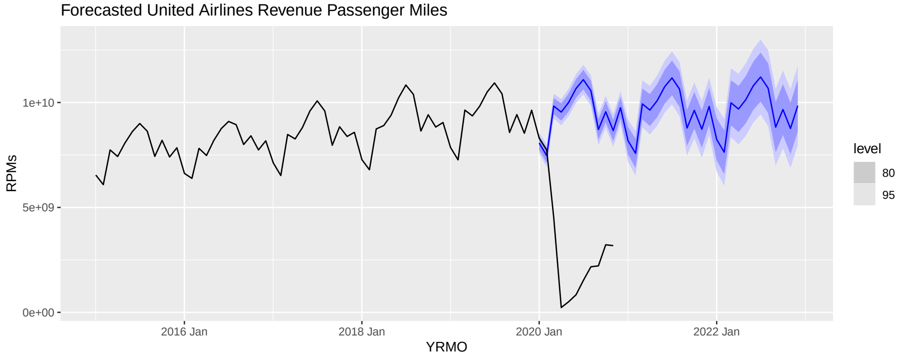
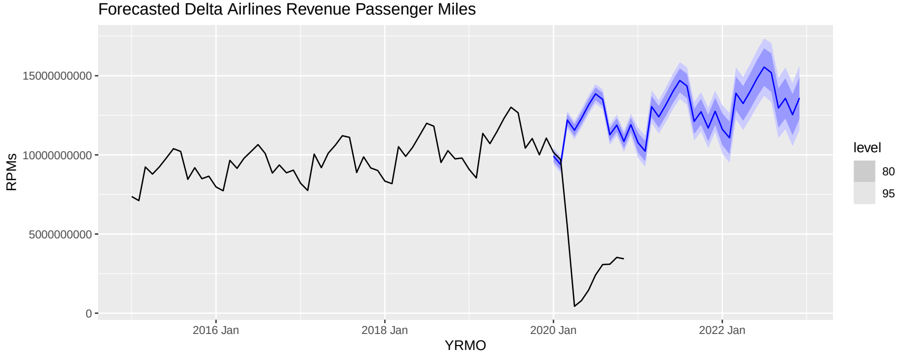
Once the residuals look like white noise, calculate forecasts.

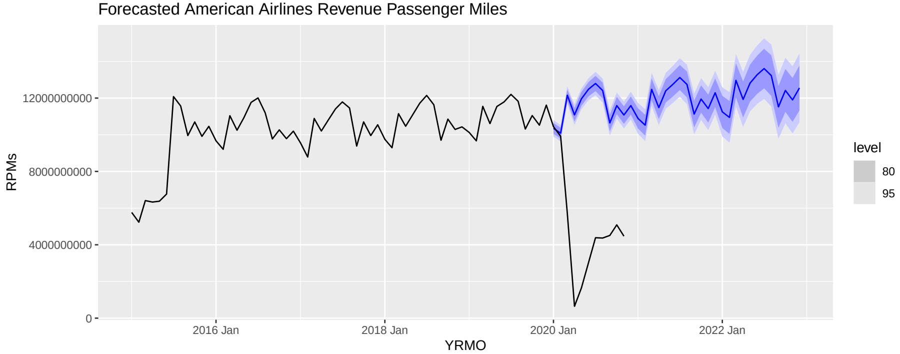
United Airlines



Delta Airlines



American Airlines



Section 4

Conclusions

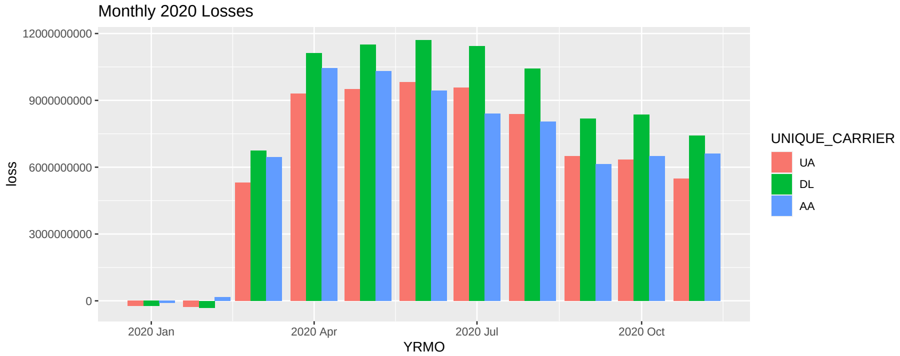
Interesting Notes

Since we have 2020 data, we can calculated "Losses" experienced by each airline with simple subtraction.

$$Loss = mean forecast for 2020 - actual RPM in 2020$$

United 2020 Losses	Delta 2020 Losses	American 2020 Losses
69726094508	86363090536	72426489751

How many Revenue Passenger Miles were lost per month in 2020?



case in point: Delta airlines lost 11.4 billion RPMs in July 2020. . . that's ***nearly 83% lost from the forecast!***

How can we measure the recovery?

Some thoughts:

- How long will it take the Big 3 to reach their pre-COVID levels? summer peak?
- How long will it take them to recoup the losses we just visualized?
- Since “Revenue Passenger Miles” are a function of dollars and passengers... can we affect dollars collected without increasing passenger counts?
- What changes in strategy could we recommend to these airlines to help them cope? (Think back to the different route/mile strategies we discussed)
- How long can they survive if passenger airline trends do not return to normal? (much harder question)