THE UNIVERSITY OF CHICAGO
GRAHAM SCHOOL OF OF CONTINUING LIBERAL AND PROFESSIONAL STUDIES
MSCA 31006 - TIME SERIES ANALYSIS AND FORECASTING

VIDEO PACKET-LOSS TIME SERIES MODELING

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Agenda

1. Problem Statement
2. Dataset Description
3. Exploratory Data Analysis
4. Proposed Models
5. Results
6. Recommendations

What is Packet Loss?

- Video packet loss occurs when one or more packets of data travelling across a network fail to reach their destination.
- Packet loss is typically caused by network congestion.
- Packet Loss = (Packet Lost/Packet Sent) x 100%

Example of packet loss effect

Source: https://en.wikipedia.org/wiki/Packet_loss

Why is it a problem?

Macro-blocking, lip sync, stuttering, smearing, freezing – the list of ways video can fail goes on and on, but it all means the same thing: your communication is interrupted, and whether it's changing the channel or picking up the phone, you must do something different.

The worrisome thing about low-quality video in the context of corporate communications is that not only do your messages fail to reach your audience, your audience starts to tune you out due to the sheer level of friction they encounter while trying to receive your messages.

For this reason, it's helpful to understand what's going on and what can be done to fix it.

The dataset

- Vidlib tool output of real-time data recorded over 2 months at every 10 ms was used.
- The packet loss data was aggregated over one hour to reduce dataset.
- A window of time of 3 weeks (01/08 – 01/29) was selected to reduce the dataset further.

	dteTime	pcktsCount	pcktsLost	packtsPcnt
1	2017-01-08 00:00:00	986.58	6.12	0.6203248
2	2017-01-08 01:00:00	984.47	7.09	0.7201845
3	2017-01-08 02:00:00	984.64	6.62	0.6723269
4	2017-01-08 03:00:00	997.94	6.20	0.6212798
5	2017-01-08 04:00:00	987.24	5.38	0.5449536
6	2017-01-08 05:00:00	976.99	5.71	0.5844482

A total of 504 regularly-spaced hourly observations

Exploratory Data Analysis

- Univariate Time Series Analysis – Only percent packet lost observations will be used for forecasting.

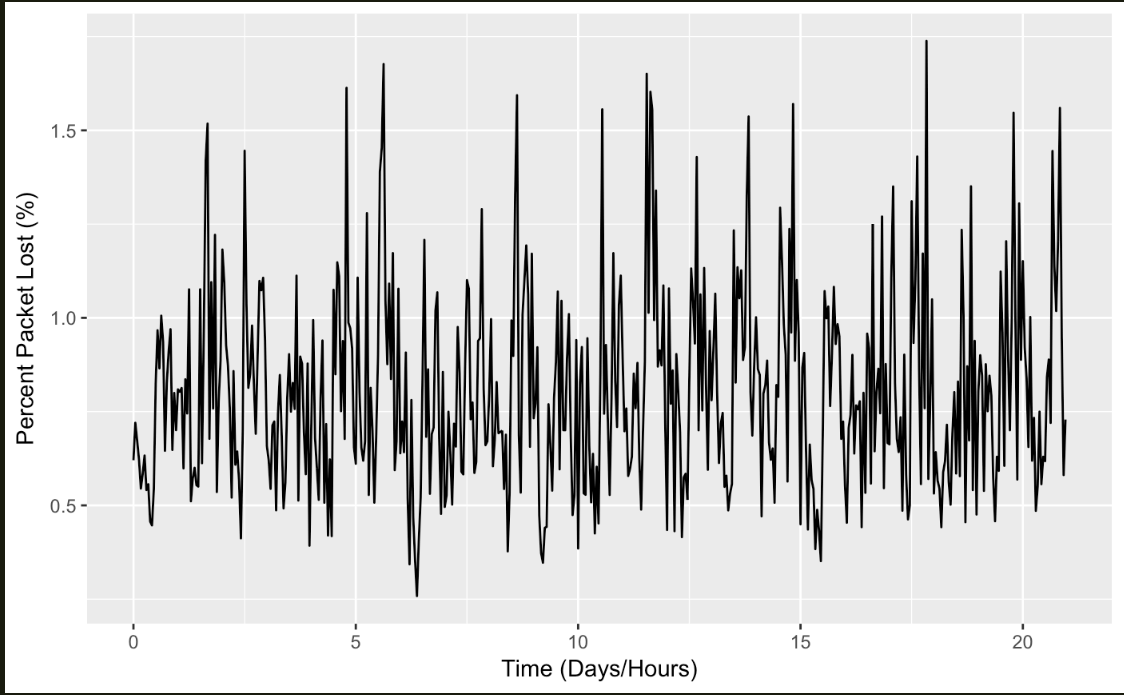
- Stationarity was initially investigated visually and through the Augmented Dickey-Fuller Test and the KPSS Test.

- Seasonality was also checked through a correlogram, a seasonal subseries plot, and a periodogram.

STATIONARITY

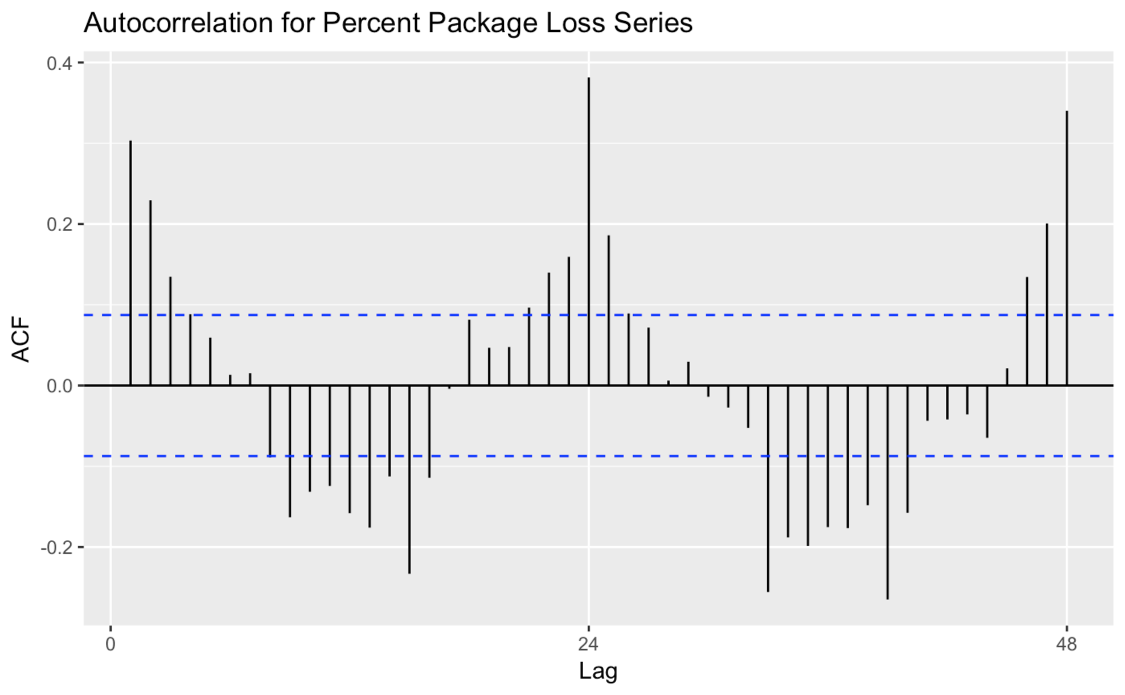
No clear trend or patterns observed.

Data appears to be stationary as confirmed by both ADF and KPSS tests.




```
        Augmented Dickey-Fuller Test

data:  pckt_data
Dickey-Fuller = -7.8037, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

```
        KPSS Test for Trend Stationarity

data:  pckt_data
KPSS Trend = 0.029491, Truncation lag parameter = 5, p-value = 0.1
```



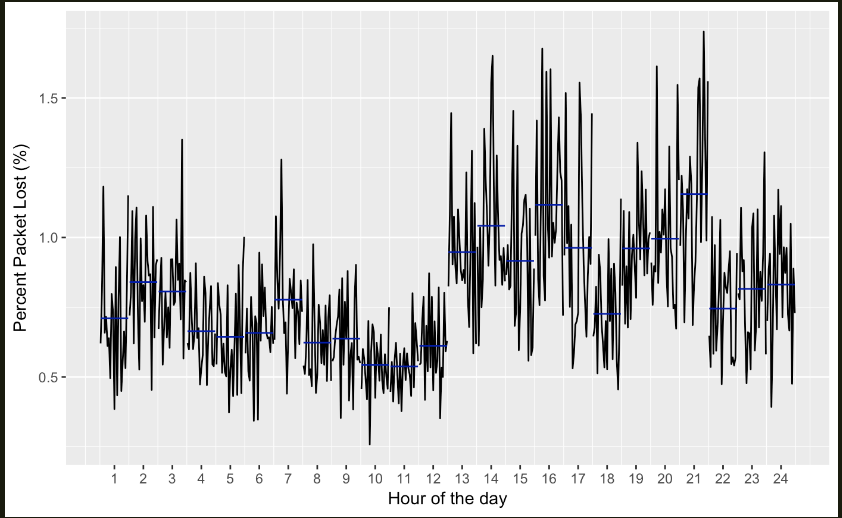
AUTO - CORRELATION

There are clear signs of autocorrelation in the data, both non-seasonal and seasonal.

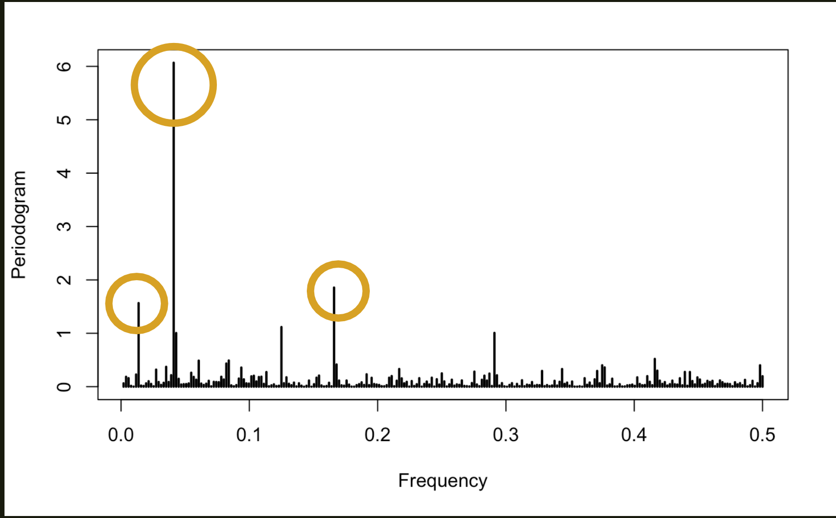
```
        Box-Ljung test

data:  .
X-squared = 46.655, df = 1, p-value = 8.466e-12
```

SEASONALITY

Seasonal Subplot



Periodogram



There appears to be a marked difference in the latter hours of the afternoon and early evening as compared to the rest of the day.

The periods corresponding to the highest spectral density

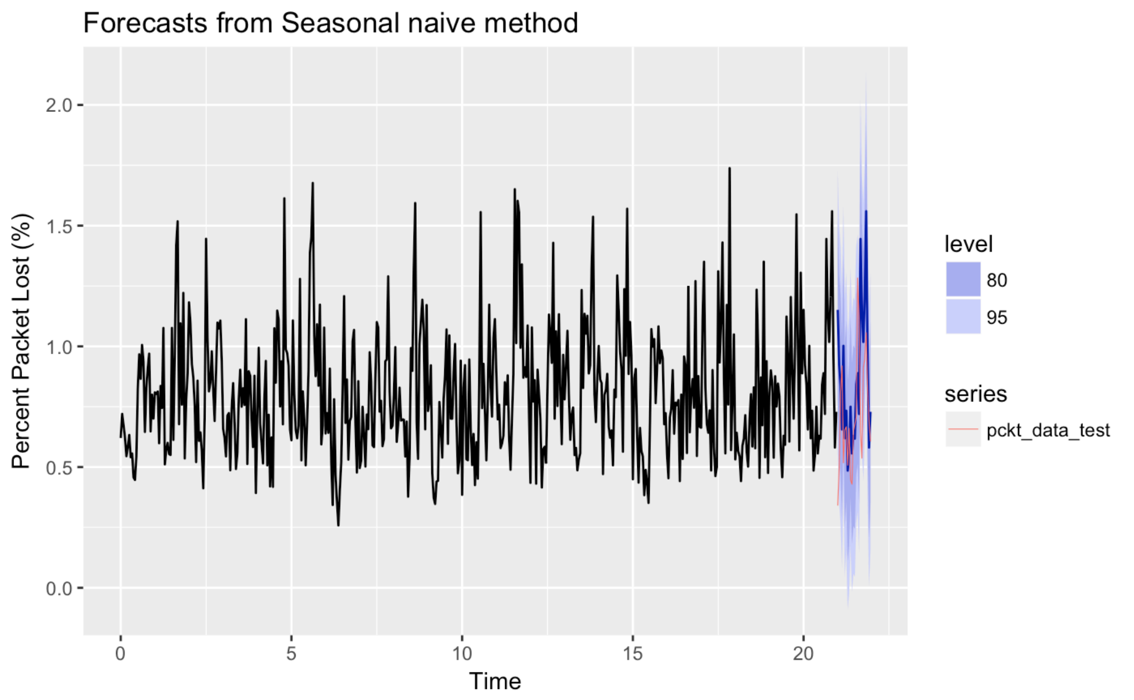
- T1 = 24.28
- T2 = 6.02
- T3 = 73.14

Proposed Modeling Approaches

- No clear approach to which model might naturally fit this dataset was identified. Thus a set of models of varying complexity were tested.

   1. Seasonal Naïve
   2. State-Space models for Exponential Smoothing
   3. Seasonal ARIMA model
   4. TBATS

- Models were evaluated on the goodness of forecasts for the next 24 hours.

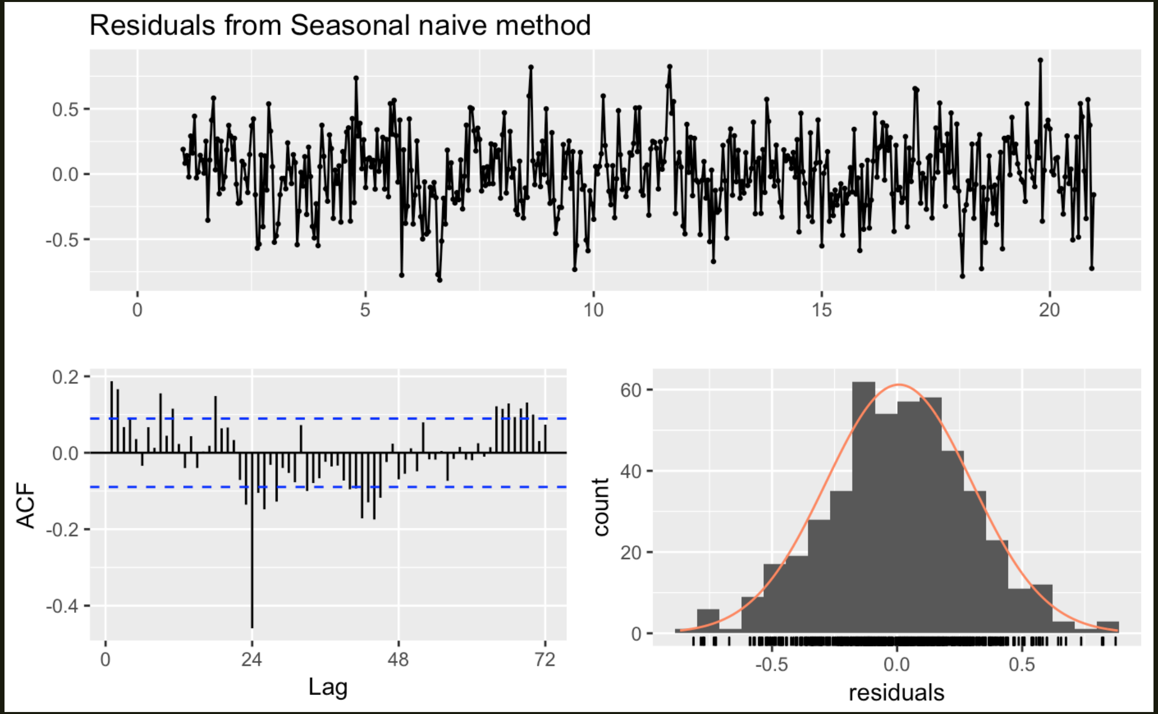


SEASONAL NAÏVE FORECAST

Seasonal naïve model works by replicating exactly the last seasonal period

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.007383779	0.2914955	0.2311604	-6.039159	30.68733	1.000000
Test set	-0.145475086	0.3528613	0.2632881	-31.596214	43.99839	1.138985

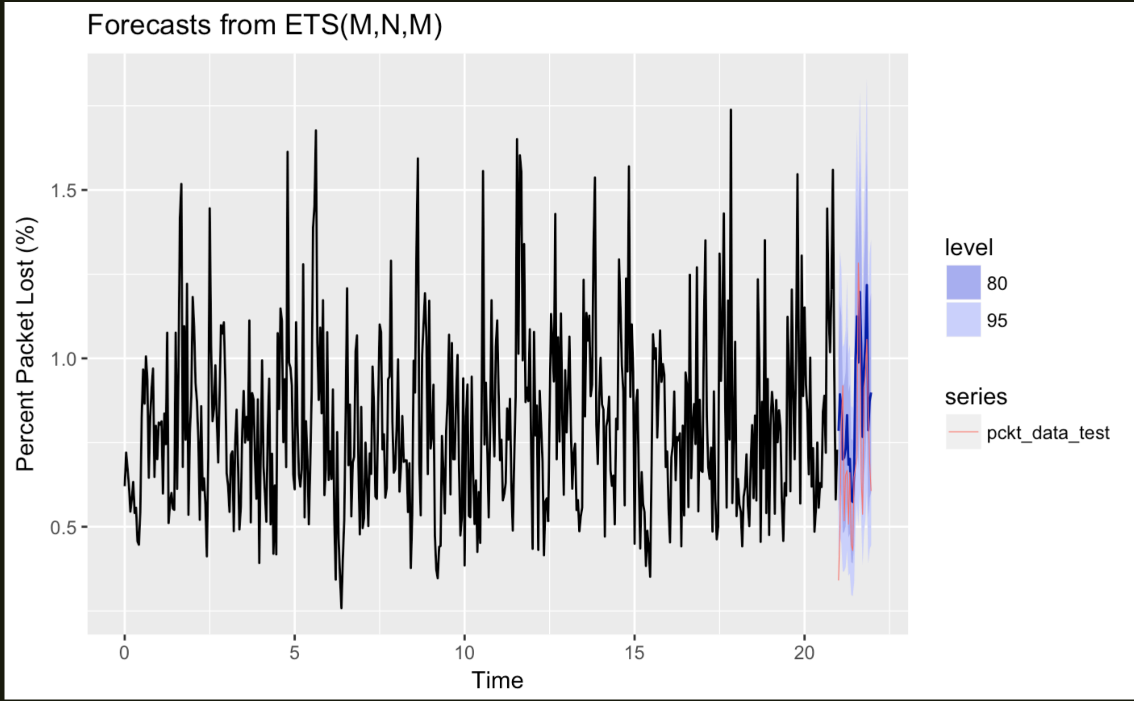
SEASONAL NAÏVE RESIDUAL ANALYSIS




```
        Ljung-Box test

data:  residuals
Q* = 306.47, df = 48, p-value < 2.2e-16

Model df: 0.   Total lags used: 48
```

Strong auto-correlation at Lag 24 not captured by model

Distribution of residual appears normal



	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.005692413	0.1988161	0.1563488	-5.167803	20.67900	0.6763651
Test set	-0.146498059	0.2319476	0.1920514	-27.910633	32.14154	0.8308148

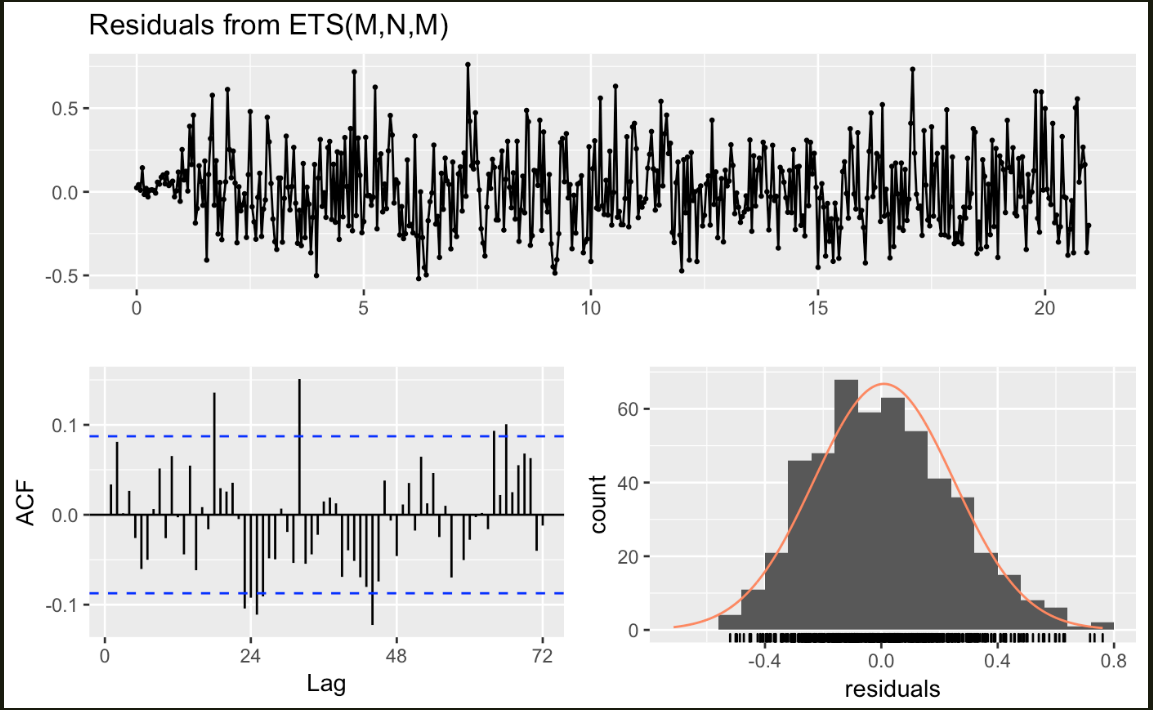
ETS FORECAST

Error/Trend/Seasonal uses State Space convention to extend Exponential Smoothing family of models

Selects best model (lowest AICc) out of 18 possible

Error – {Additive, Multiplicative}
Trend - {None, Additive, Additive Damped)
Seasonality – {None, Additive, Multiplicative}

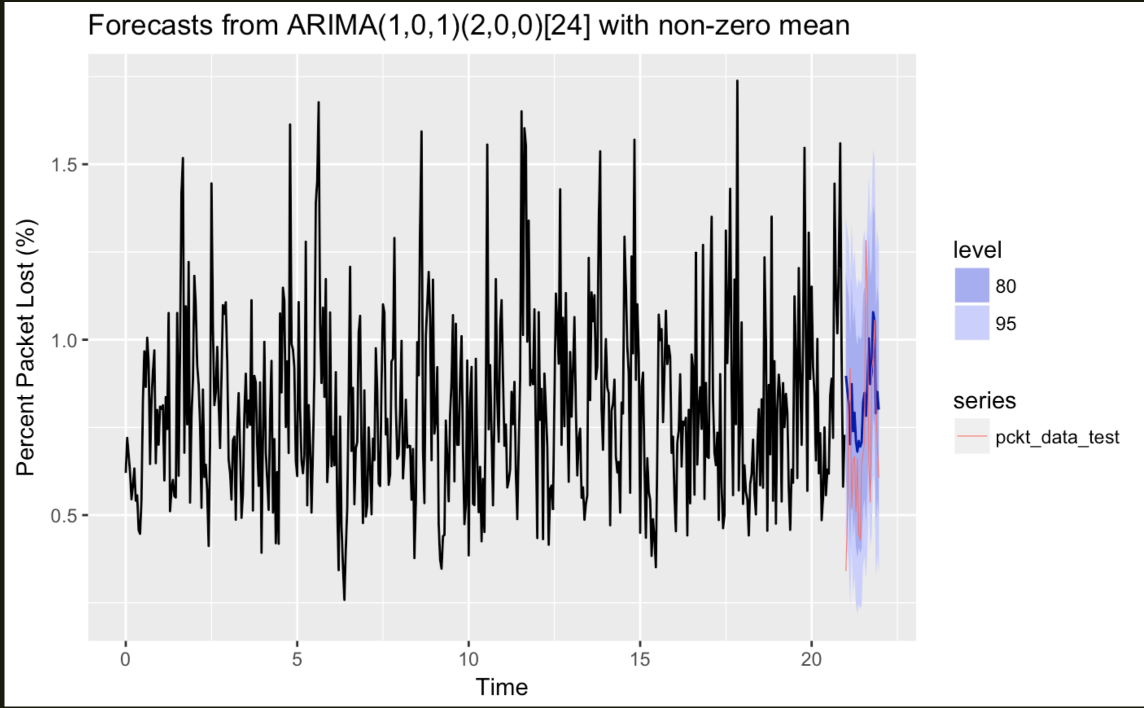
ETS RESIDUAL ANALYSIS




```
        Ljung-Box test

data:  residuals
Q* = 93.432, df = 22, p-value = 8.871e-11

Model df: 26.   Total lags used: 48
```

Autocorrelation improved, fewer smaller spikes. However, fails Ljung-Box test

Distribution of residuals appears normal and tighter



	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.001963561	0.2270144	0.1780557	-7.828116	23.97321	0.7702693
Test set	-0.115330883	0.2503180	0.1998090	-27.143646	34.65398	0.8643741

ARIMA FORECAST

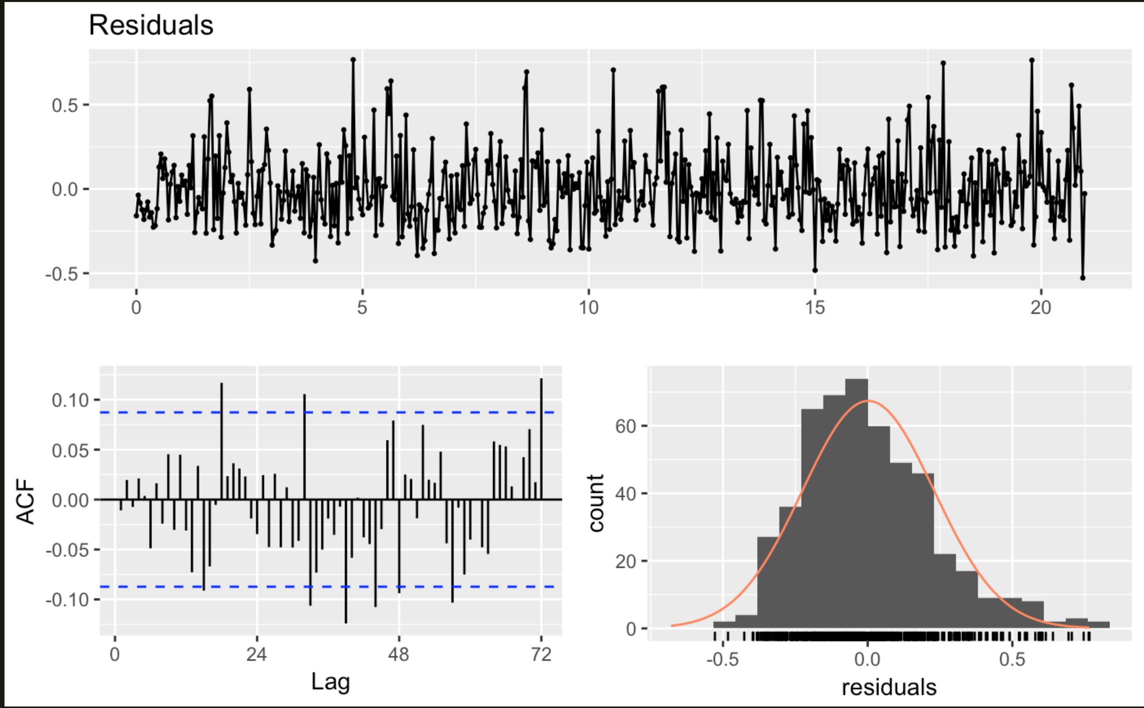
ARIMA models forecast future points by regressing on multiple lagged observations and/or errors.

SARIMA model composed of:

ARMA (1,1) for non-seasonal

AR(2) for seasonal

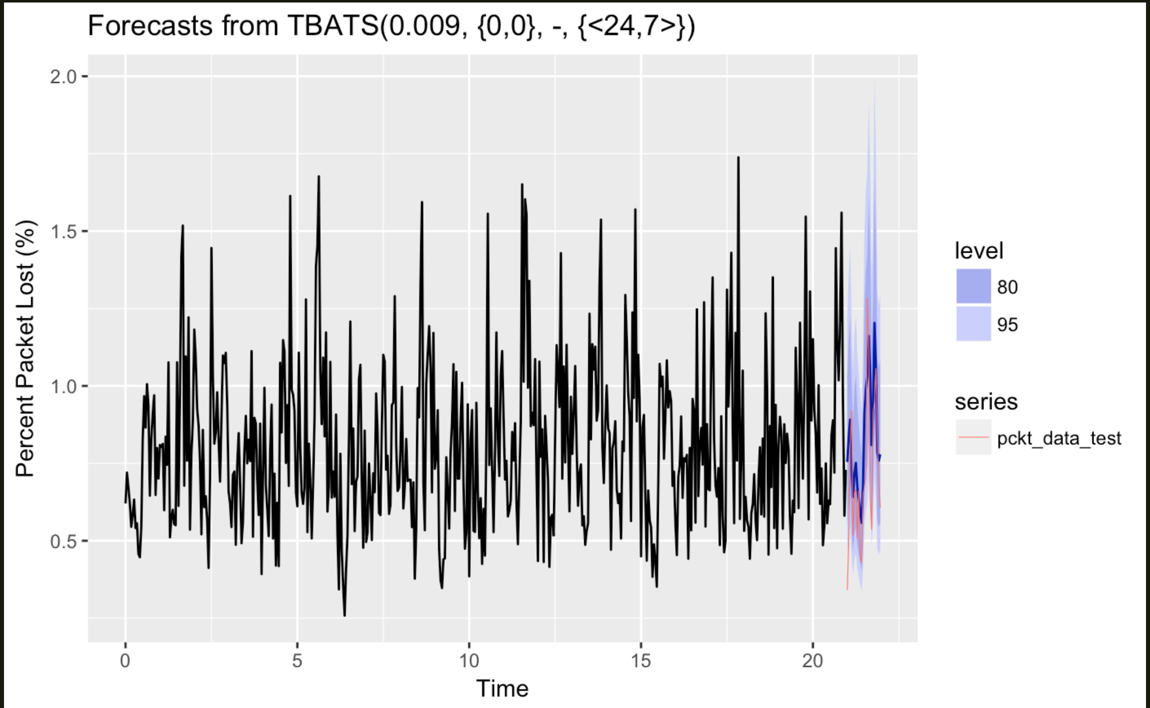
ARIMA RESIDUAL ANALYSIS




```
        Ljung-Box test

data:  residuals
Q* = 77.309, df = 43, p-value = 0.001028

Model df: 5.   Total lags used: 48
```

Less autocorrelation in this mode, bigger p-value from Ljung-Box test

Distribution appears to be a little skew, model might be biased.



	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.02633079	0.2050179	0.1574748	-2.629472	20.20505	0.6812360
Test set	-0.11678586	0.1989356	0.1582125	-23.103819	27.08748	0.6844277

TBATS FORECAST

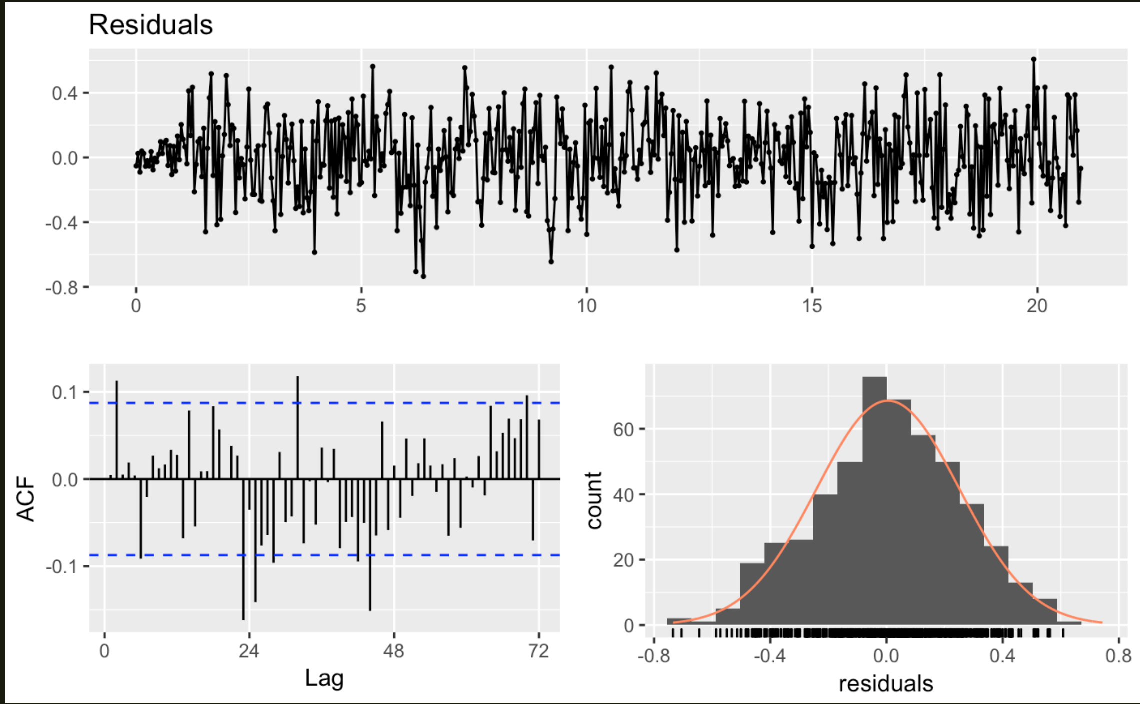
Trigonometric
7 Fourier-like terms selected

Box-Cox
Lambda = 0.009

ARMA
{p,q} = {0,0}

Trend
- No damping

Seasonal
24




```
        Ljung-Box test

data:  residuals
Q* = 109.82, df = 29, p-value = 2.474e-11

Model df: 19.   Total lags used: 48
```

TBATS RESIDUAL ANALYSIS

Autocorrelation is still present

Residuals have a very nice normal distribution

Results

- TBATS model was the best performing model overall in minimizing error with respect to the test sample.
- ARIMA model was superior in capturing autocorrelation in the residuals.
- Overall the models appear to have more forecasting power than a simple seasonal naïve prediction.

Model	**RMSE**	**Ljung-Box Q**
Seasonal Naive	0.352	306.4
ETS	0.231	93.4
ARIMA	0.250	77.3
TBATS	0.198	109.8

Recommendations

- TBATS model had a better performance overall in reducing forecast error and better predictive power (similar level of errors in training and holdout sets).

- Further investigation in prediction accuracy can be achieved using different validation techniques: i.e cross-validation (forecast evaluation on a rolling origin).

- Searching for covariates which might affect the packet loss percentage.

THANK YOU!

QUESTIONS?