Time Series Forecasting: Machine Learning and Deep Learning with R & Python

Marco Zanotti

University of Milan

2021/2022

Part I

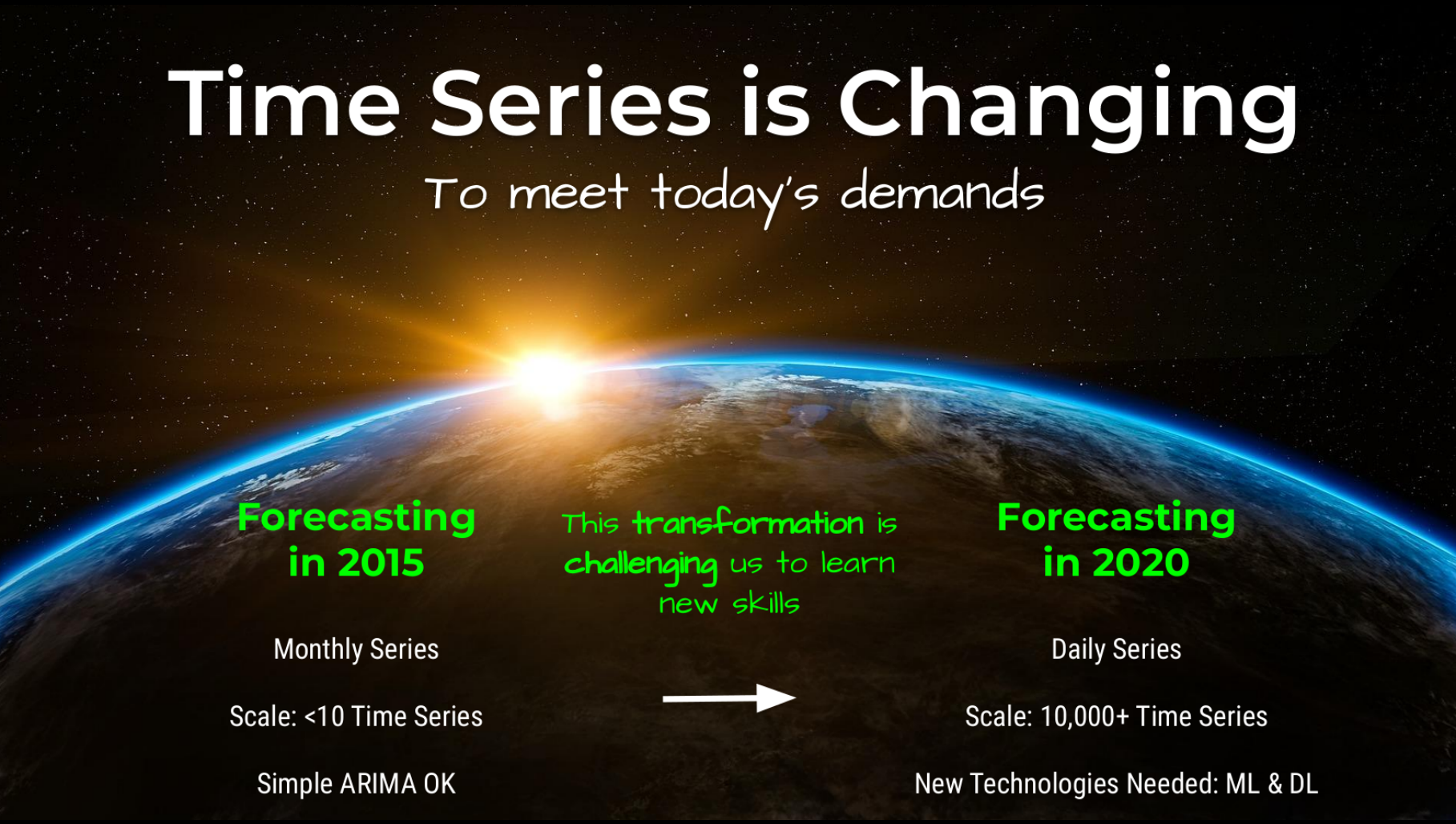
Time Series Forecasting in 2022

Business Forecasting is Changing

1. Higher frequencies.
2. Scale is increasing.
3. Automation is needed.

Time Series is Changing

To meet today's demands



Forecasting in 2015

Monthly Series

Scale: <10 Time Series

Simple ARIMA OK

This **transformation** is **challenging** us to learn new skills

Forecasting in 2020

Daily Series

Scale: 10,000+ Time Series

New Technologies Needed: ML & DL

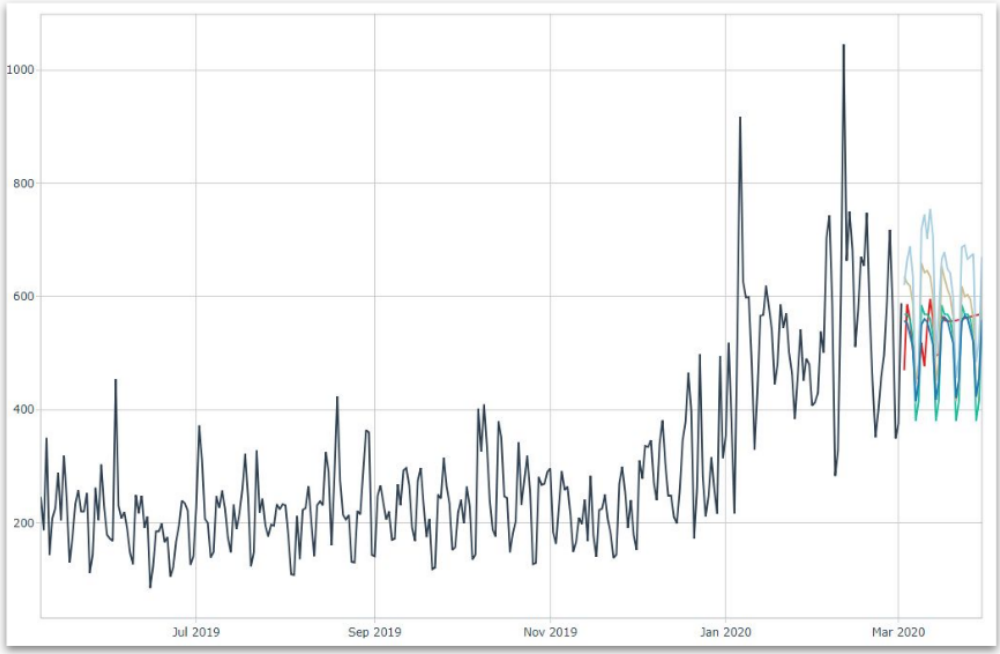

Your Organization:
“I need a data scientist that knows time series, can improve forecasting, and I need it done for **10,000+ Time Series every day.**”

What are they asking for?

"I need a data scientist that knows time series, can improve forecasting, and I need it done for **10,000+ Time Series every day.**"

What I really meant to say is, **"I need you to make a High-Performance Forecasting System (HPFS)."**

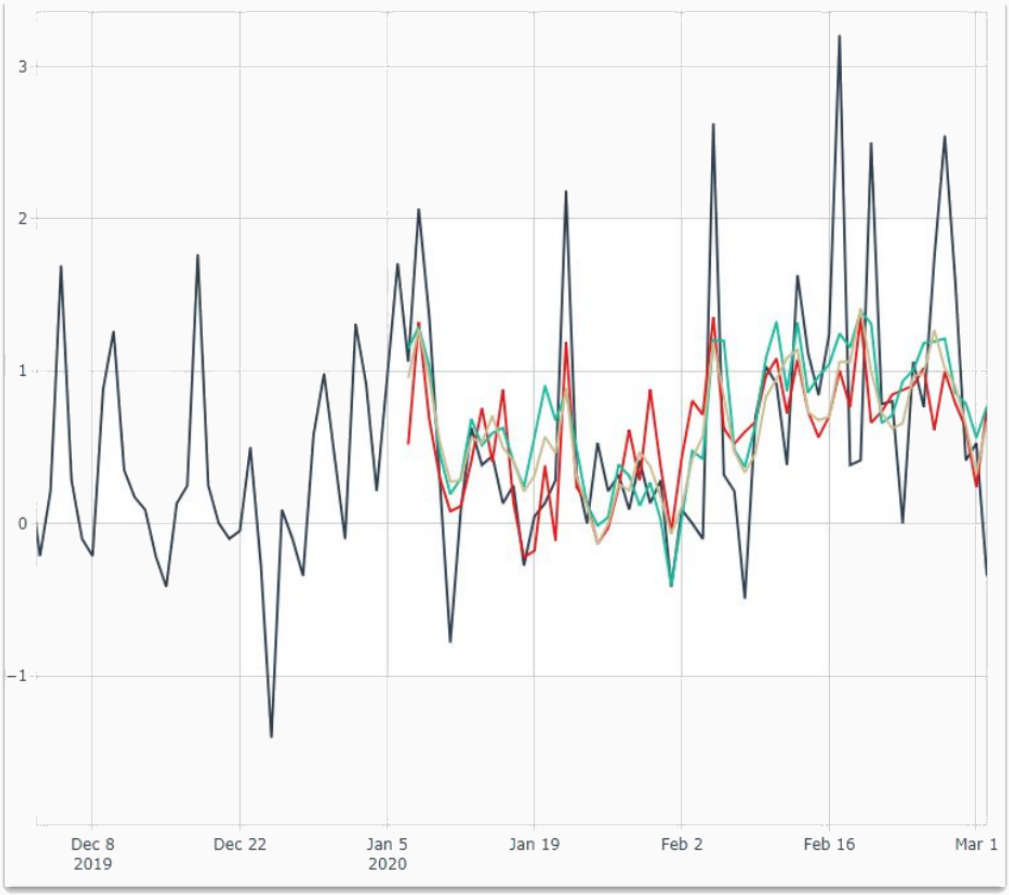
HPFS
=
This...
x 10,000



3 Properties of

High-Performance Forecasting Systems

What companies want



1. Improves Results

Improvements of 10% save organizations **Millions of $$$**

This is why the organization **invests in you.**

Property #1: Delivers the Best Possible Results Given Your Resource Constraints

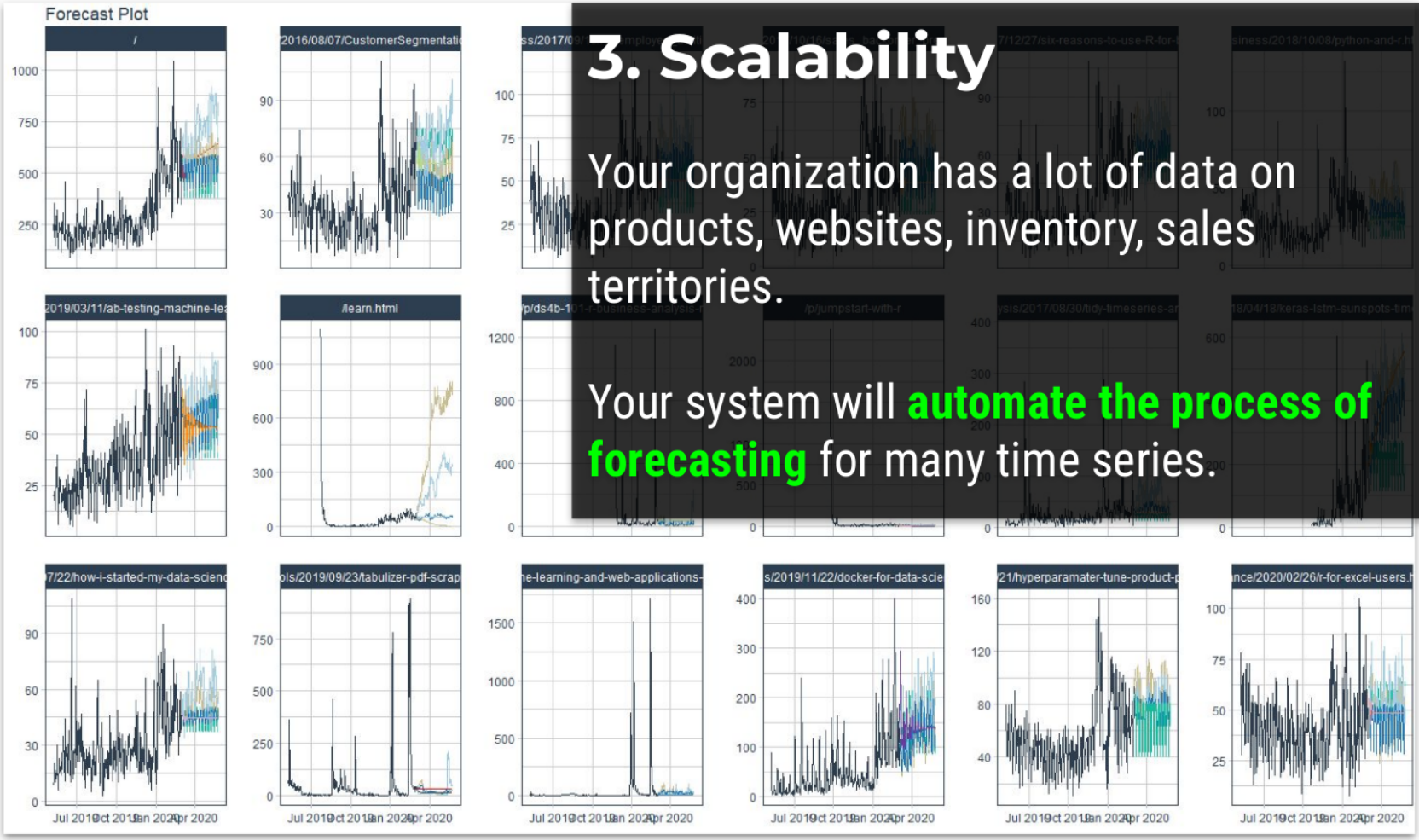
.model_id	.model_desc	.type	mae	mape	mase	smape	rmse	rsq
21	PROPHET W/ XGBOOST ERRORS	Test	0.46	1519.18	0.62	85.54	0.63	0.44
14	XGBOOST - Lag	Test	0.48	891.48	0.66	90.59	0.65	0.4
20	PROPHET W/ REGRESSORS	Test	0.49	1435.07	0.66	87.04	0.66	0.39
19	NNAR(2,1,10)[7]	Test	0.51	1377.19	0.69	96.09	0.69	0.33
2	GLMNET - Lag	Test	0.52	1286.65	0.7	98.93	0.7	0.36
16	CUBIST - Lag	Test	0.53	1364.64	0.71	96.51	0.7	0.32
7	KERNLAB - Spline	Test	0.52	1180.45	0.7	97.06	0.71	0.34
8	KERNLAB - Lag	Test	0.53	1200.72	0.72	100.76	0.71	0.34
12	RANDOMFOREST - Lag	Test	0.52	843	0.7	96.48	0.71	0.37
28	SEASONAL DECOMP: REGRESSION WITH ARIMA(2,1,3) ERRORS	Test	0.53	1058.11	0.71	101.56	0.71	0.32
3	EARTH - Spline	Test	0.52	1051.52	0.7	91.72	0.72	0.28
18	NNET - Lag	Test	0.59	1884.91	0.8	92.29	0.72	0.35
22	REGRESSION WITH ARIMA(2,1,1)(0,0,2)[7] ERRORS	Test	0.56	2206.12	0.76	86.77	0.72	0.31
1	GLMNET - Spline	Test	0.54	1222.27	0.73	102.76	0.73	0.3
4	EARTH - Lag	Test	0.52	570.12	0.71	105.52	0.73	0.36
23	ARIMA(2,1,2) W/ XGBOOST ERRORS	Test	0.52	1473.81	0.71	102.71	0.73	0.34
25	TBATS(1, {0,2}, -, {<7,2>, <30,6>, <365,8>})	Test	0.52	990.87	0.71	93.43	0.74	0.3
9	KKNN - Spline	Test	0.56	1279.32	0.76	98.45	0.75	0.25
17	NNET - Spline	Test	0.55	1838.88	0.75	90.6	0.75	0.19
27	SEASONAL DECOMP: ARIMA(3,1,3)	Test	0.57	946.13	0.77	109.56	0.76	0.26

2. Report Accuracy

Your organization needs to know if there is an issue with the system.

Which time series?
Which models?

Property #2: Reports accuracy & Alerts if an issue is detected



3. Scalability

Your organization has a lot of data on products, websites, inventory, sales territories.

Your system will **automate the process of forecasting** for many time series.

Property #3: Scalable from One to Many Time Series

Part II

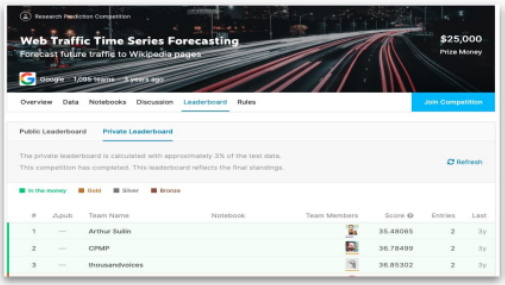
Competitions

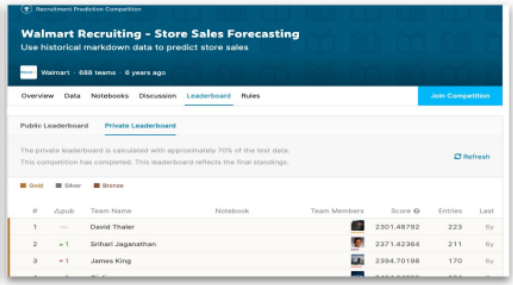
Competition Review

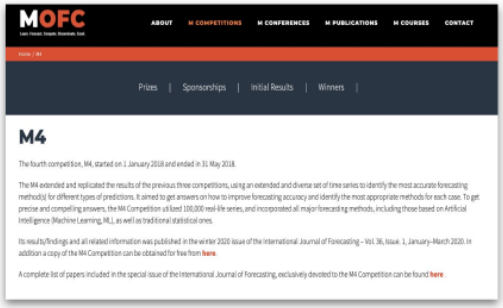
Competitions have the exact properties we are looking for:

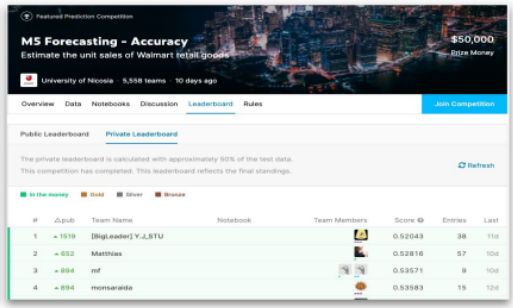
- Scalability
- Maximize Results
- Report Accuracy

Learn from competitions.









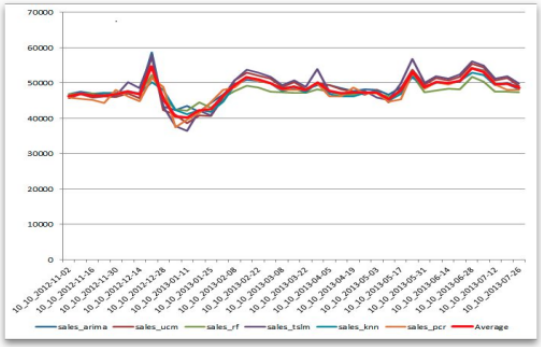
Forecasting Competitions	Year Held
Walmart Recruiting - Store Sales Forecasting	2014
M4 Competition - 100,000 Univariate Time Series	2018
Wikipedia Website Traffic Forecast Competition	2018
M5 Competition - Walmart	2020

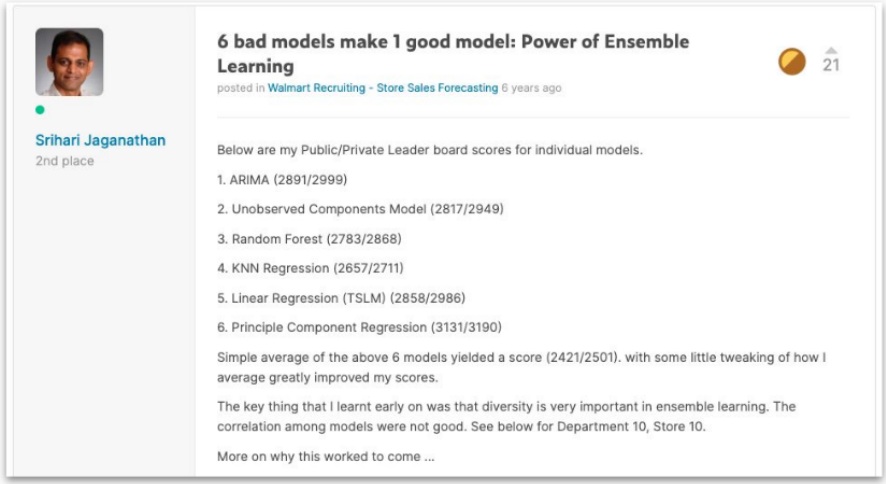
Walmart Sales (2014): 2nd Place Solution - Machine Learning & Ensembling 6 Bad Models Make 1 Good One!

Ensembling Different ML Approaches using Calendar (Date) Features

- ARIMA (2891 / 2999)
- Random Forest (2783 / 2868)
- KNN Regression (2657 / 2858)
- +3 More ML / Univariate Models

Simple Average (2371)





6 bad models make 1 good model: Power of Ensemble Learning

posted in Walmart Recruiting - Store Sales Forecasting 6 years ago

21

Srihari Jaganathan
2nd place

Below are my Public/Private Leader board scores for individual models.

1. ARIMA (2891/2999)
2. Unobserved Components Model (2817/2949)
3. Random Forest (2783/2868)
4. KNN Regression (2657/2711)
5. Linear Regression (TSLM) (2858/2986)
6. Principle Component Regression (3131/3190)

Simple average of the above 6 models yielded a score (2421/2501). with some little tweaking of how I average greatly improved my scores.

The key thing that I learnt early on was that diversity is very important in ensemble learning. The correlation among models were not good. See below for Department 10, Store 10.

More on why this worked to come ...

Pros:
Easy to automate using Classical + ML + Date Features + Ensembling (Model Averaging)

Cons: Didn't detect the Key Event (Shift in Holiday Spending)

Website Traffic Forecasting: 1st Place Solution - Deep Learning RNN

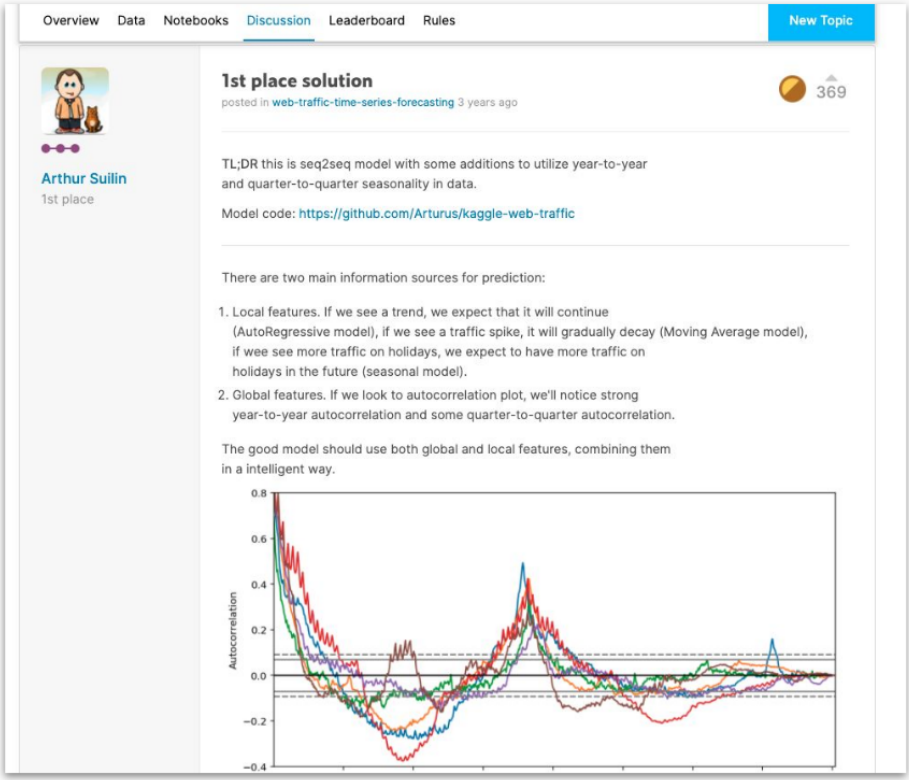
RNN using features:

- Yearly Seasonality
- Holidays

LSTM can accept multiple features, which is very powerful for learning using autocorrelation.

"...[RNN] a natural extension of ARIMA models, but much more flexible & expressive."

- Arthur Suilin



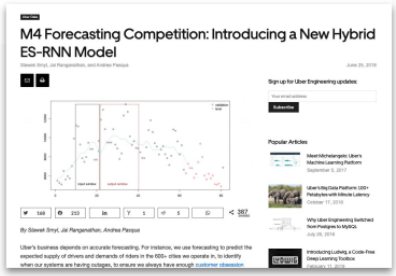
M4 Competition: 1st Place - Deep Learning Hybrid

Key to the victory
Combining Deep Learning with Exponential Smoothing

Won by 3%
(big margin vs 2nd Place)

In more recent news, **N-Beats RNN algorithm** is reported to have improved an additional 3% over ES-RNN Hybrid model.

Author(s)	Affiliation	sMAPE	MASE	OWA	Rank			% improvement method over the benchm	
					sMAPE	MASE	OWA	sMAPE	MASE
Smyl	Uber Technologies	11.374	1.536	0.821	1	1	1	9.4	7.7
Montero-Manso, et al.	University of A Coruña & Monash University	11.720	1.551	0.838	3	3	2	6.6	6.7
Pawlikowski, et al.	ProLogistica Soft	11.845	1.547	0.841	5	2	3	5.7	6.9



M5 Competition: 1st Place - Feature Engineering

Feature Engineering

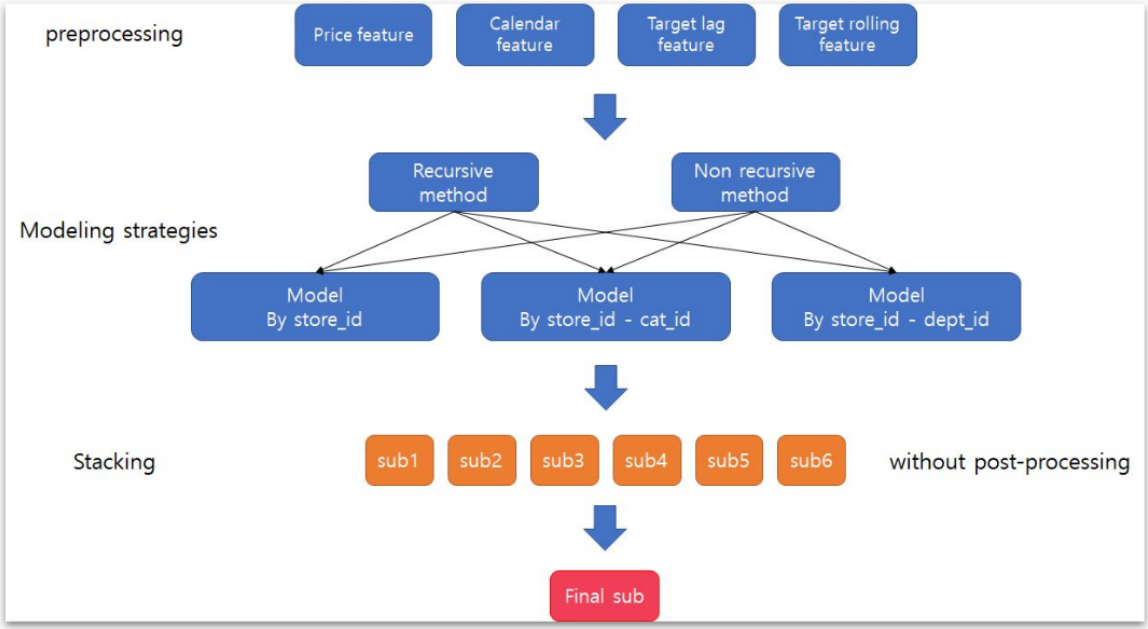
- Price
- Calendar Features
- Lag Features
- Rolling Lags

Machine Learning:

LightGBM

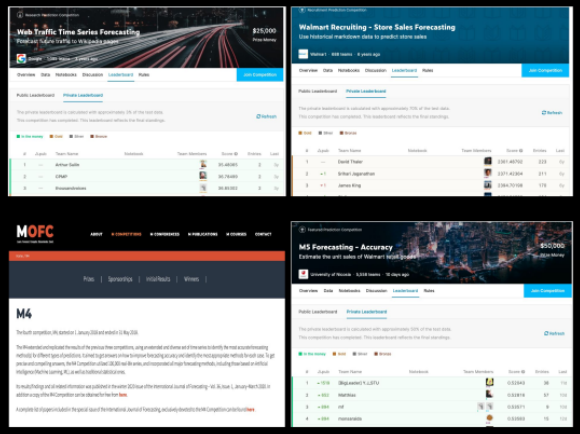
Ensembling (Stacking):

Led to robustness



5 Competition Takeaways

The techniques that will lead to a **high-performance forecasting system.**



1. **Feature engineering.** 1st Place & 3rd Place in 2020 M5 Walmart Challenge. Calendar-Features, Lags.

2. **Experimentation and ensembling.** 1st Place in 2020 M5 Walmart Competition. 2nd Place in 2014 Walmart Challenge (almost won it).

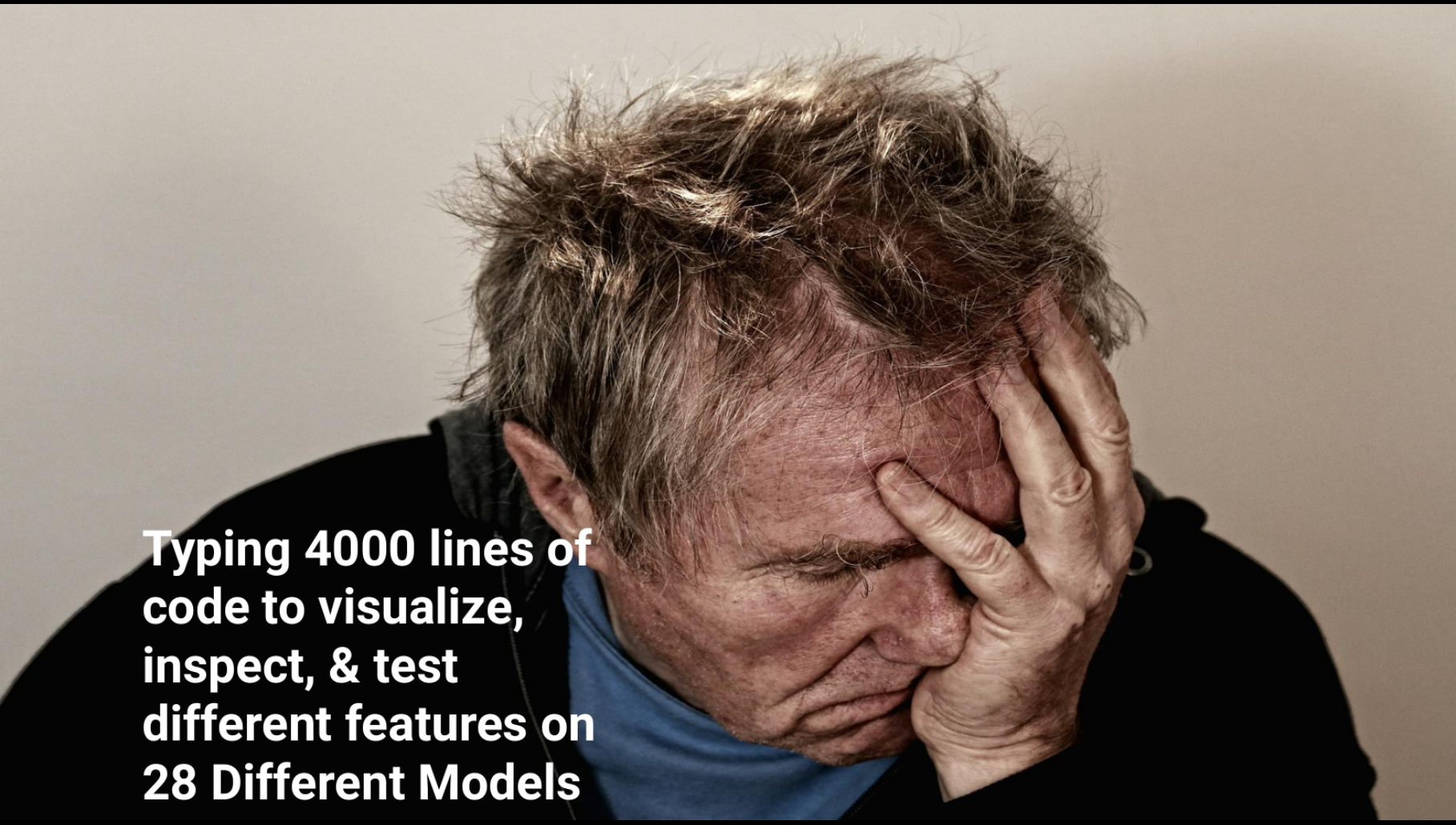
3. **Knowledge of key events.** Shift in holiday sales improved accuracy 12% in 2014 Walmart Challenge, landing 1st place spot.

4. **Machine Learning.** Machine Learning claimed 1st Place in 2020 M5 Competition. 2nd Place in 2014 Walmart Challenge.

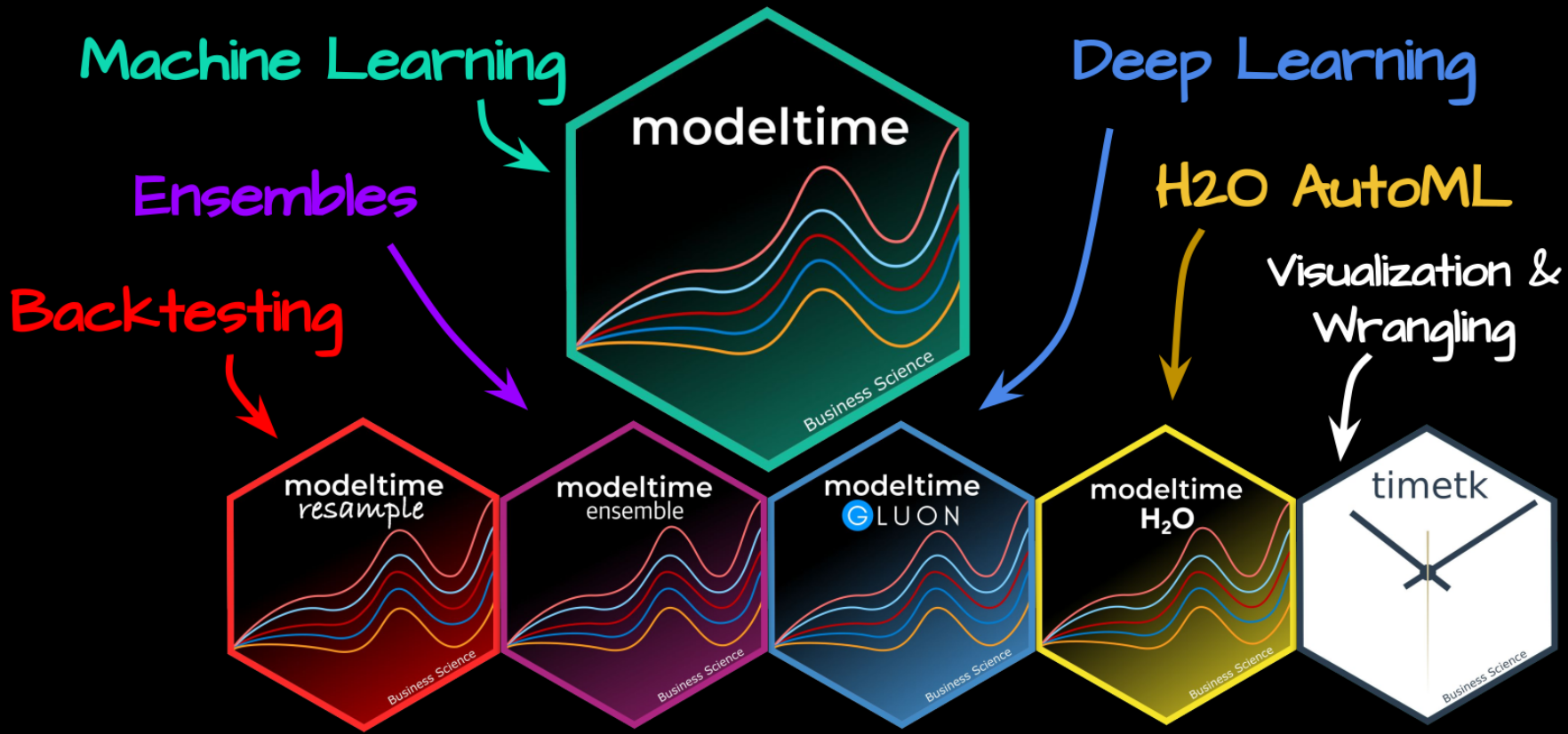
5. **Deep Learning.** Recurrent Neural Networks (RNNs) won 2018 M4 & Wikipedia Competitions. Also performed well in 2020 M5 Competition.

Part III

Modeltime


Typing 4000 lines of
code to visualize,
inspect, & test
different features on
28 Different Models

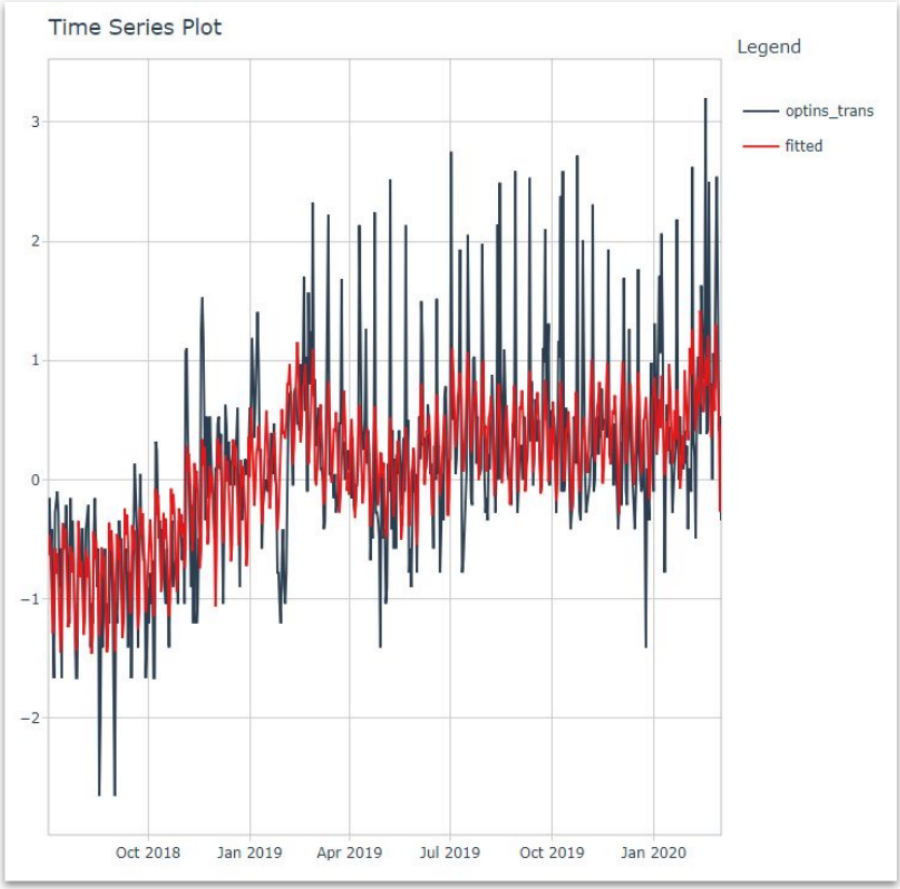

Typing 2000 lines of
code to make a
multi-model forecast


Machine Learning
Deep Learning
Ensembles
H2O AutoML
Backtesting
Visualization &
Wrangling
modeltime
Business Science
modeltime
resample
Business Science
modeltime
ensemble
Business Science
modeltime
GLUON
Business Science
modeltime
H2O
Business Science
timetk
Business Science

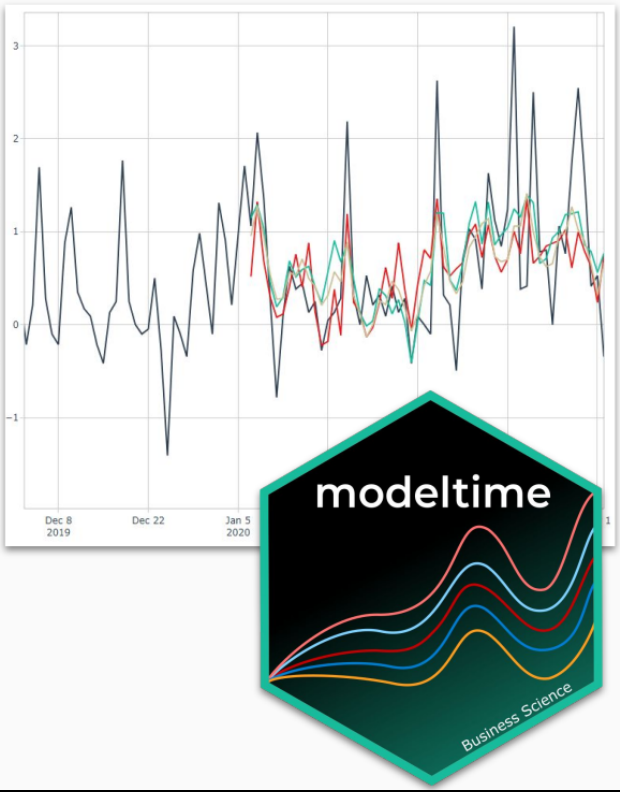
Feature Engineering

```
134 data_prep_signature_tbl %>%
135     plot_time_series_regression(
136         optin_time,
137         .formula = model_fomula_seasonality,
138         .show_summary = TRUE
139     )
```

```
Residual standard error: 0.6023 on 580 degrees of freedom
Multiple R-squared:  0.4869,    Adjusted R-squared:  0.4621
F-statistic: 19.65 on 28 and 580 DF,  p-value: < 2.2e-16
```

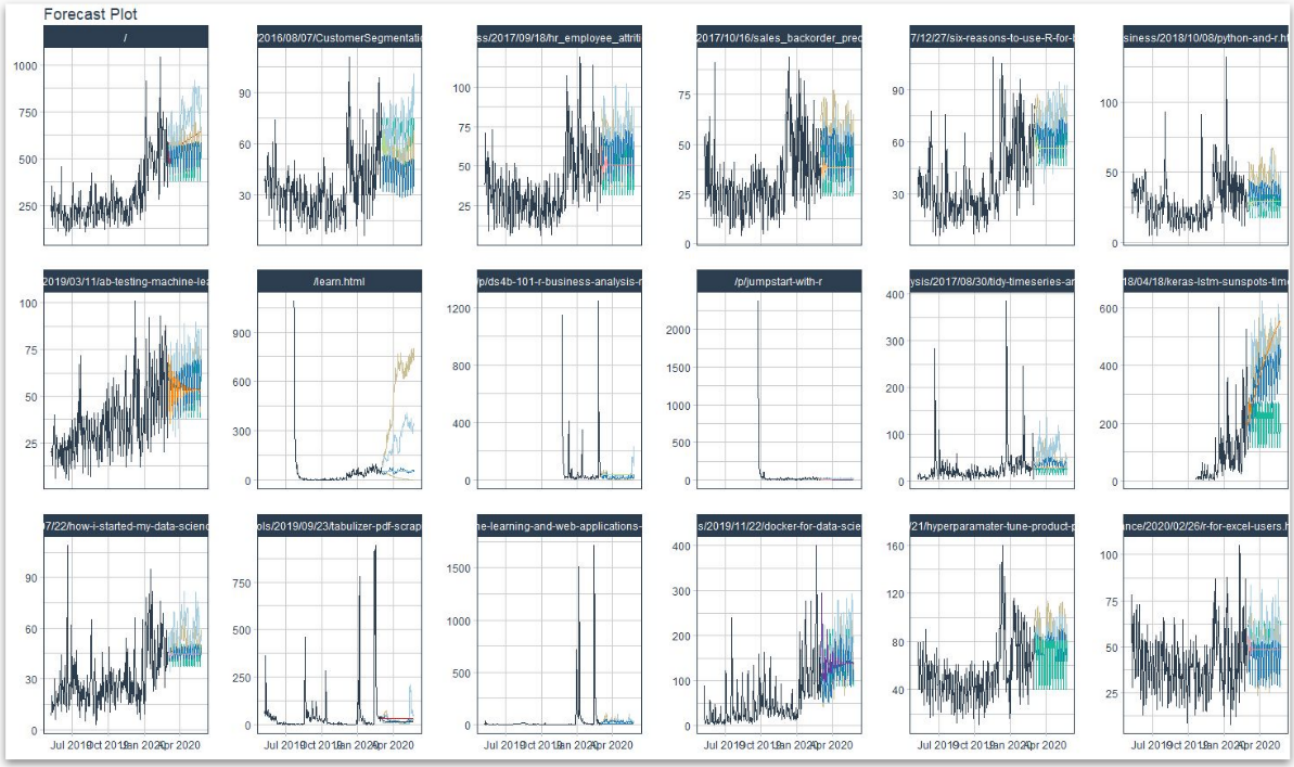


Multi-Model Experiments



.model_id	.model_desc	.type	mae	mape	mase	smape	rmse	rsq
21	PROPHET W/ XGBOOST ERRORS	Test	0.46	1519.18	0.62	85.54	0.63	0.44
14	XGBOOST - Lag	Test	0.48	891.48	0.66	90.59	0.65	0.4
20	PROPHET W/ REGRESSORS	Test	0.49	1435.07	0.66	87.04	0.66	0.39
19	NNAR(2,1,10)[7]	Test	0.51	1377.19	0.69	96.09	0.69	0.33
2	GLMNET - Lag	Test	0.52	1286.65	0.7	98.93	0.7	0.36
16	CUBIST - Lag	Test	0.53	1364.64	0.71	96.51	0.7	0.32
7	KERNLAB - Spline	Test	0.52	1180.45	0.7	97.06	0.71	0.34
8	KERNLAB - Lag	Test	0.53	1200.72	0.72	100.76	0.71	0.34
12	RANDOMFOREST - Lag	Test	0.52	843	0.7	96.48	0.71	0.37
28	SEASONAL DECOMP: REGRESSION WITH ARIMA(2,1,3) ERRORS	Test	0.53	1058.11	0.71	101.56	0.71	0.32
3	EARTH - Spline	Test	0.52	1051.52	0.7	91.72	0.72	0.28
18	NNET - Lag	Test	0.59	1884.91	0.8	92.29	0.72	0.35
22	REGRESSION WITH ARIMA(2,1,1)(0,0,2)[7] ERRORS	Test	0.56	2206.12	0.76	86.77	0.72	0.31
1	GLMNET - Spline	Test	0.54	1222.27	0.73	102.76	0.73	0.3
4	EARTH - Lag	Test	0.52	570.12	0.71	105.52	0.73	0.36
23	ARIMA(2,1,2) W/ XGBOOST ERRORS	Test	0.52	1473.81	0.71	102.71	0.73	0.34
25	TBATS(1, {0,2}, -, {<7,2>, <30,6>, <365,8>})	Test	0.52	990.87	0.71	93.43	0.74	0.3
9	KKNN - Spline	Test	0.56	1279.32	0.76	98.45	0.75	0.25
17	NNET - Spline	Test	0.55	1838.88	0.75	90.6	0.75	0.19
27	SEASONAL DECOMP: ARIMA(3,1,3)	Test	0.57	946.13	0.77	109.56	0.76	0.26

Scalable Forecasting with Ensembles



TRUE

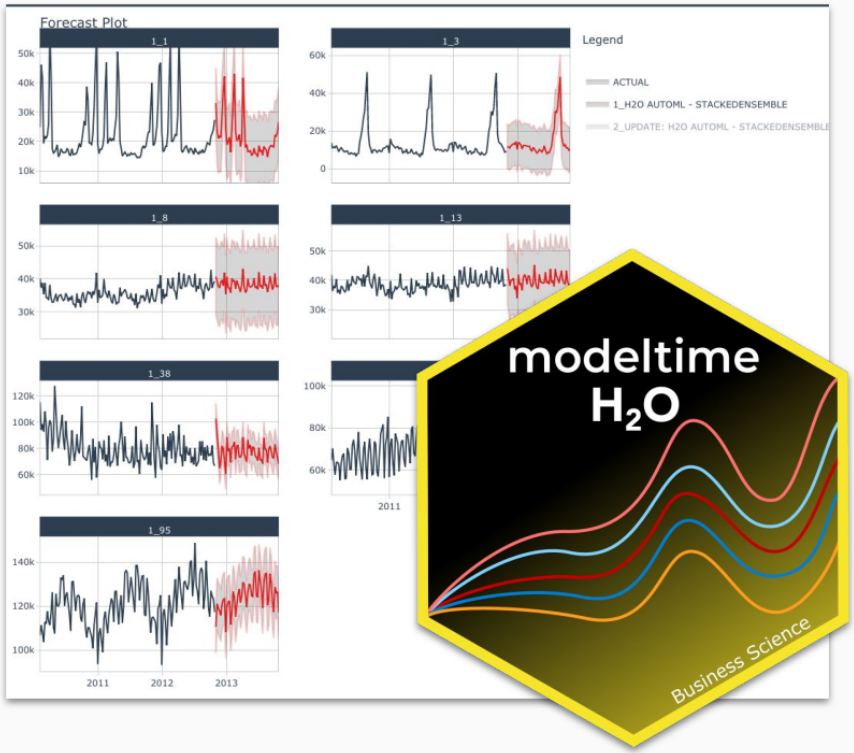
```
[25]: t0 <- Sys.time()
      model_fit_deepar <- deep_ar(
        id                    = "id",
        freq                  = "M",
        prediction_length     = 24,
        lookback_length       = 36,
        epochs                = 1,
        num_batches_per_epoch = 500,
        learn_rate            = 0.001,
        num_layers            = 3,
        num_cells             = 80,
        dropout               = 0.10
      ) %>%
        set_engine("gluonts_deepar") %>%
        fit(value ~ date + id, training(m750_splits))

      t1 <- Sys.time()
      t1-t0

      Execution started at 2021-03-05 17:31:47

      Time difference of 44.16673 secs
```

GluonTS Deep Learning for Forecasting

```
# A tibble: 32 x 6
   model_id                       mean_residual_devi…  rmse      mse    mae rmsle
   <chr>                                     <dbl> <dbl>    <dbl>  <dbl> <dbl>
 1 StackedEnsemble_AllModels_A…          36291288. 6024.  3.63e7 3626. 0.147
 2 StackedEnsemble_BestOfFamil…          37802329. 6148.  3.78e7 3709. 0.149
 3 XGBoost_grid__1_AutoML_2021…          38139582. 6176.  3.81e7 3767. 0.153
 4 XGBoost_grid__1_AutoML_2021…          38195759. 6180.  3.82e7 3738. 0.157
 5 XGBoost_grid__1_AutoML_2021…          39154490. 6257.  3.92e7 3959. 0.156
 6 XGBoost_grid__1_AutoML_2021…          39757275. 6305.  3.98e7 3953. 0.156
 7 XGBoost_3_AutoML_20210406_1…          40117557. 6334.  4.01e7 3841. 0.154
 8 XGBoost_grid__1_AutoML_2021…          40380426. 6355.  4.04e7 3915. 0.160
 9 GBM_grid__1_AutoML_20210406…          41239637. 6422.  4.12e7 3801. 0.161
10 GBM_1_AutoML_20210406_140637          41610511. 6451.  4.16e7 3994. 0.172
# … with 22 more rows
```

H2O.ai

Unlocks the power of **H2O AutoML** inside of Modeltime



Lot’s of models available

Lot's of models available

modeltime::prophet_reg()
- Prophet

modeltime::arima_reg()
- Auto ARIMA
- ARIMA

modeltime::exp_smoothing()
- ETS
- CROSTON
- Theta

modeltime::seasonal_reg()
- TBATS
- STLM

modeltime::nnetar()
- NNETAR

modeltime::prophet_boost()
- Prophet + XGBoost

modeltime::arima_boost()
- Auto ARIMA + XGBoost
- ARIMA + XGBoost

modeltime::window_reg()
- Window Function Models

modeltime::naive_reg()
- Naive
- Seasonal Naive

Modeltime Algorithm List

Lot's of models available

modeltime.gluonts::deep_ar()

- GluonTS Deep AR
- Torch Deep AR

modeltime.gluonts::nbeats()

- GluonTS N-BEATS
- GluonTS N-BEATS Ensemble

modeltime.gluonts::deep_state()

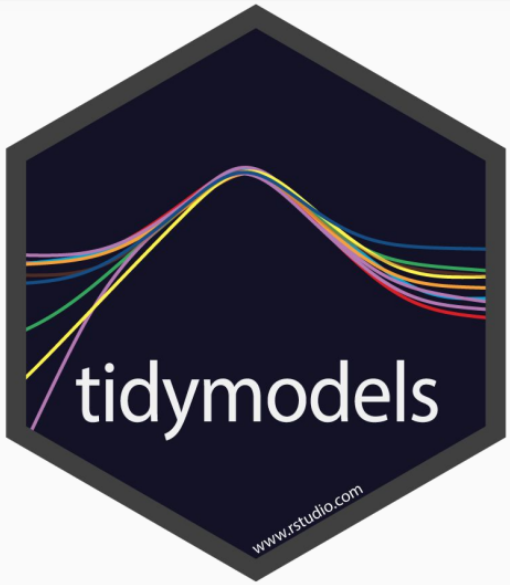
- GluonTS Deep State

modeltime::gp_forecaster()

- GluonTS GP Forecaster

Modeltime Gluonts Algorithm List

Lot’s of models available



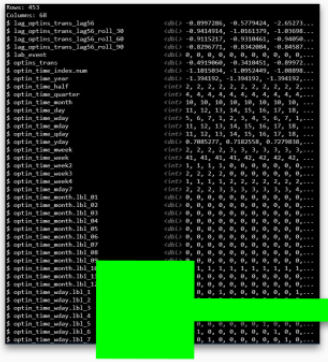
Parsnip Models List

- XGBoost
- Decision Trees
- GAMS
- Linear Regression
- MARS
- Neural Networks
- K-Nearest Neighbors
- Random Forest
- Support Vector Machines
- & more!

Community contributed Modeltime Extensions!

A lot to learn to Time Series

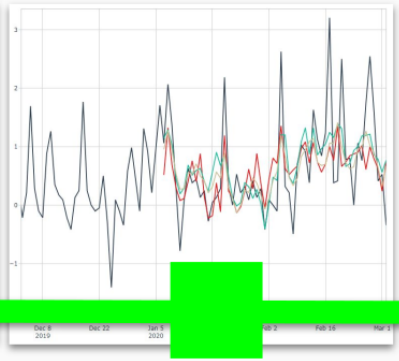
Feature Engineering



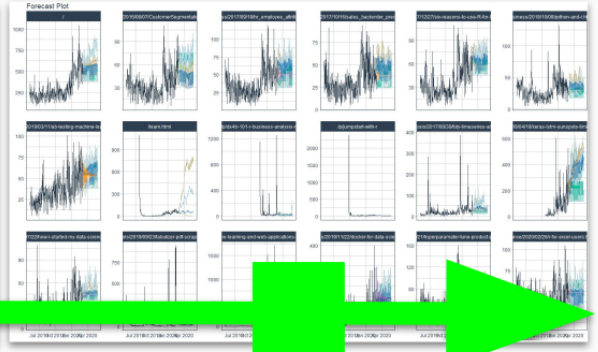
Modeling & Experimentation

.model_id	.model_desc	.type	mae	mape	mase	smape	rmse	rsq
21	PROPHET W/ XGBOOST ERRORS	Test	0.46	1519.18	0.62	85.54	0.63	0.44
14	XGBOOST - Lag	Test	0.48	891.48	0.66	90.59	0.65	0.4
20	PROPHET W/ REGRESSORS	Test	0.49	1435.07	0.66	87.04	0.66	0.39
19	NNAR(2,1,10)[7]	Test	0.51	1377.19	0.69	96.09	0.69	0.33
2	GLMNET - Lag	Test	0.52	1286.65	0.7	98.93	0.7	0.36
16	CUBIST - Lag	Test	0.53	1364.64	0.71	96.51	0.7	0.32
7	KERNLAB - Spline	Test	0.52	1180.45	0.7	97.06	0.71	0.34
8	KERNLAB - Lag	Test	0.53	1200.72	0.72	100.76	0.71	0.34
12	RANDOMFOREST - Lag	Test	0.52	843	0.7	96.48	0.71	0.37
28	SEASONAL DECOMP - REGRESSION WITH ARIMA(2,1,3) ERRORS	Test	0.53	1058.11	0.71	101.56	0.73	0.32
3	EARTH - Spline	Test	0.52	1051.52	0.7	91.72	0.72	0.28
18	NNET - Lag	Test	0.59	1884.91	0.8	92.29	0.72	0.35
22	REGRESSION WITH ARIMA(2,1,1) (0,0,2)[7] ERRORS	Test	0.56	2206.12	0.76	86.77	0.72	0.31
1	GLMNET - Spline	Test	0.54	1222.27	0.73	102.76	0.73	0.3
4	EARTH - Lag	Test	0.52	570.12	0.71	105.52	0.73	0.36
23	ARIMA(2,1,2) W/ XGBOOST ERRORS	Test	0.52	1473.81	0.71	102.71	0.73	0.34
25	TBATS(1, {0,2}, -, {<7.2>, <30.6>, <365.8>})	Test			0.71	93.43	0.74	0.3
9	KKNN - Spline	Test			0.76	98.45	0.75	0.25
27	SEASONAL DECOMP - ARIMA(3,1,3)	Test			0.77	109.16	0.78	0.24

Tuning & Cross Validation



Scaling to 1000s of Time Series



MODELTIME Workflow

Create Modeltime Table
`modeltime_table()`

```
# Modeltime Table
# A tibble: 5 x 3
  .model_id .model   .model_desc
      <int> <list>   <chr>
1         1 <fit[+]> ARIMA(0,1,1)(0,1,1)[12]
2         2 <fit[+]> ARIMA(0,1,1)(0,1,1)[12] W/ XGBOOST ERRORS
3         3 <fit[+]> ETS(M,A,A)
4         4 <fit[+]> LM
5         5 <fit[+]> EARTH
```

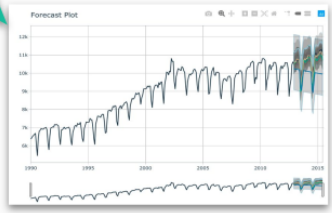
Calibrate
`modeltime_calibrate()`

```
# Modeltime Table
# A tibble: 6 x 5
  .model_id .model   .model_desc                          .type .calibration_data
      <int> <list>   <chr>                                <chr> <list>
1         1 <fit[+]> ARIMA(0,1,1)(0,1,1)[12]              Test  <tibble [31 × 4]>
2         2 <fit[+]> ARIMA(0,1,1)(0,1,1)[12] W/ XGBOOST ERRORS Test  <tibble [31 × 4]>
3         3 <fit[+]> ETS(M,A,A)                           Test  <tibble [31 × 4]>
4         4 <fit[+]> PROPHET                              Test  <tibble [31 × 4]>
5         5 <fit[+]> LM                                   Test  <tibble [31 × 4]>
6         6 <fit[+]> EARTH                                Test  <tibble [31 × 4]>
```

Refit
`modeltime_refit()`

```
# Modeltime Table
# A tibble: 6 x 5
  .model_id .model   .model_desc                          .type .calibration_data
      <int> <list>   <chr>                                <chr> <list>
1         1 <fit[+]> ARIMA(0,1,1)(0,1,1)[12]              Test  <tibble [31 × 4]>
2         2 <fit[+]> ARIMA(0,1,1)(0,1,1)[12] W/ XGBOOST ERRORS Test  <tibble [31 × 4]>
3         3 <fit[+]> ETS(A,A,A)                           Test  <tibble [31 × 4]>
4         4 <fit[+]> PROPHET                              Test  <tibble [31 × 4]>
5         5 <fit[+]> LM                                   Test  <tibble [31 × 4]>
6         6 <fit[+]> EARTH                                Test  <tibble [31 × 4]>
```

Forecast Test Set
`modeltime_forecast()`



`plot_modeltime_forecast()`

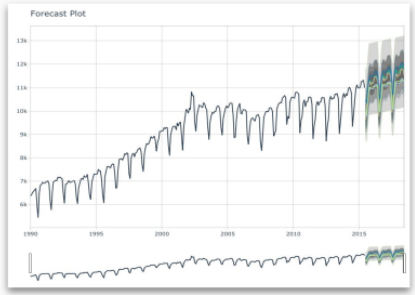
Test Accuracy
`modeltime_accuracy()`

Accuracy Table

.model_id	.model_desc	.type	mae	mape	mase	smape	rmse	rsq
1	ARIMA(0,1,1)(0,1,1)[12]	Test	151.33	1.41	0.52	1.43	197.71	0.93
2	ARIMA(0,1,1)(0,1,1)[12] W/ XGBOOST ERRORS	Test	147.04	1.37	0.50	1.39	191.84	0.93
3	ETS(M,A,A)	Test	77.00	0.73	0.26	0.73	90.27	0.98
4	PROPHET	Test	177.51	1.70	0.61	1.70	234.65	0.88
5	LM	Test	629.12	6.01	2.15	5.81	657.19	0.91
6	EARTH	Test	709.83	6.59	2.42	6.86	782.82	0.55

`table_modeltime_accuracy()`

Forecast Future
`modeltime_forecast()`



`plot_modeltime_forecast()`

Part IV

Recursivity

Why Recursive Forecasting?

It started with ARIMA

Topics

Autocorrelation & Lags

AR & MA Models (ARIMA)

Differencing (ARIMA)

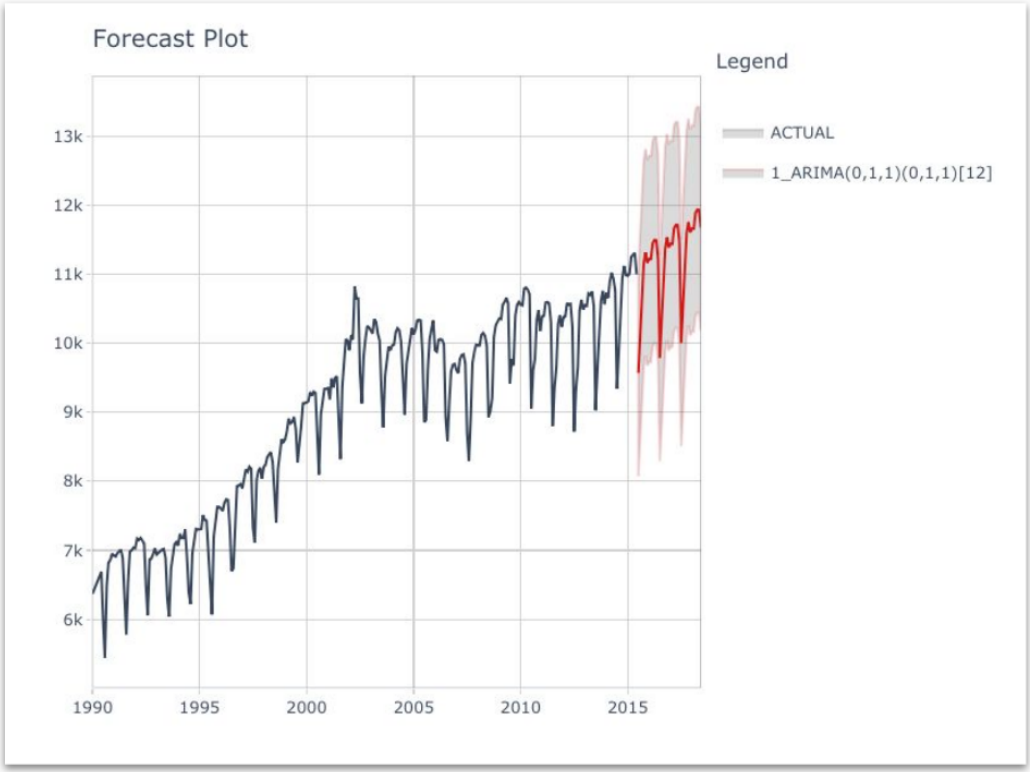
Seasonal ARIMA (SARIMA)

X-Regs (ARIMAX)

Automated Model Selection

Strengths & Weaknesses

What is ARIMA?



Autocorrelation and Lags

Time Series often have relationship to what happened previously. This relationship can be exploited.

Lagged correlations can be used to iteratively predict steps forward. And **lagged errors** as well.

Auto ARIMA automates the process of finding the optimal model that represents the structure using both Lagged Features and Lagged Error terms.

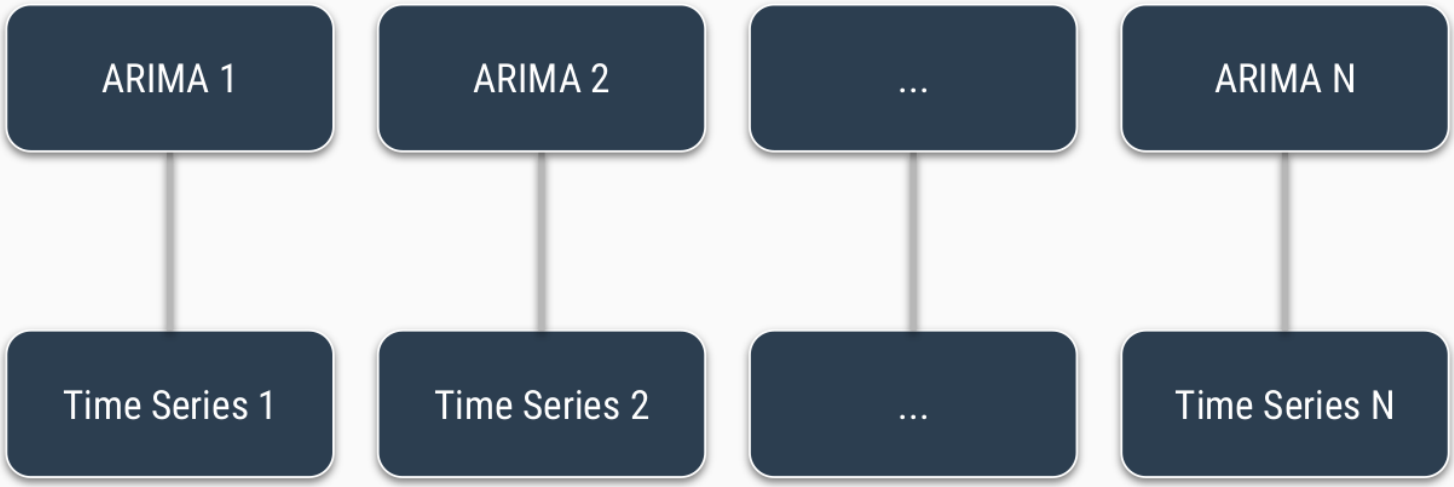
Date	Value	$Value_{t-1}$	$Value_{t-2}$
1/1/2017	200	NA	NA
1/2/2017	220	200	NA
1/3/2017	215	220	200
1/4/2017	230	215	220
1/5/2017	235	230	215
1/6/2017	225	235	230
1/7/2017	220	225	235
1/8/2017	225	220	225
1/9/2017	240	225	220
1/10/2017	245	240	225

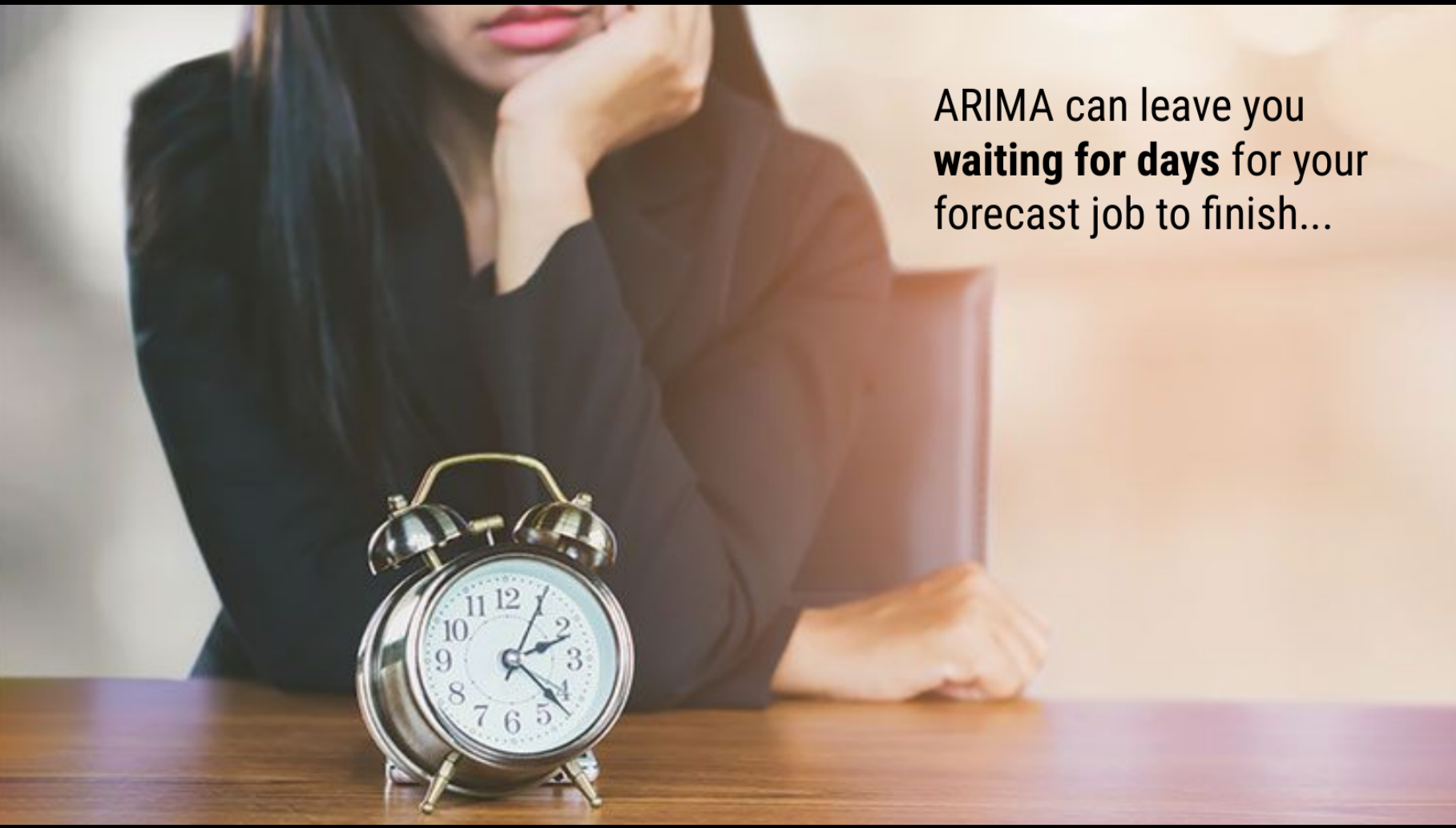
$$value_t \sim b_1 value_{t-1} + b_2 value_{t-2}$$

Problem

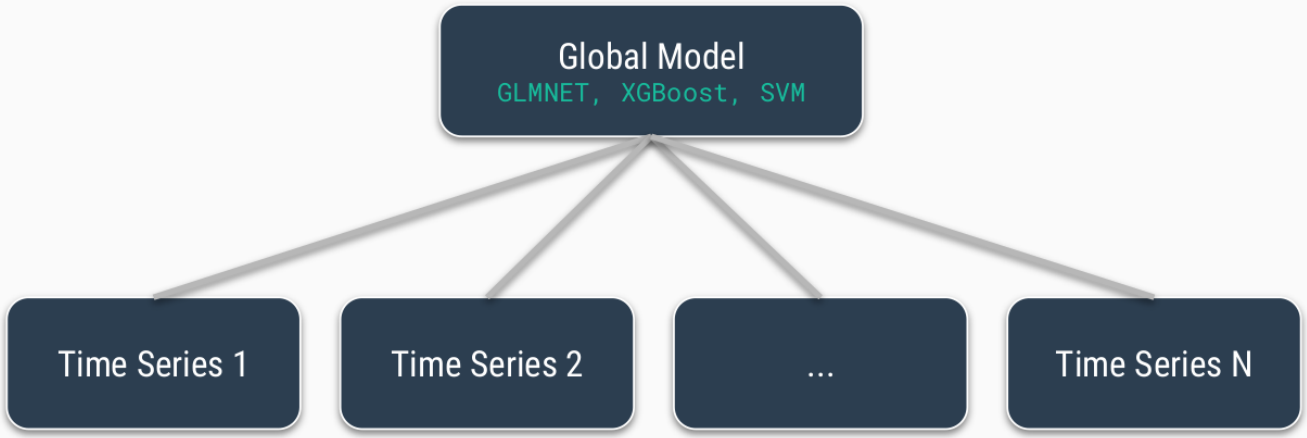
ARIMA has a **big problem**

18 Time Series requires
18 different ARIMA Models




ARIMA can leave you
waiting for days for your
forecast job to finish...

Solution: Global Models



This sounds great until you realize, your future data has Missing Values

```
> data_future_tbl %>% select(source_key, date, value, starts_with("value_lag"))
# A tibble: 432 x 27
   source_key     date       value value_lag1 value_lag2 value_lag3 value_lag4 value_lag5 value_lag6 value_lag7 value_lag8
   <chr>          <date>     <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>
 1 ELEC.GEN.ALL-… 2021-02-01    NA     350815     344970     302702     313910     334270     399504     414243     352766
 2 ELEC.GEN.ALL-… 2021-03-01    NA         NA     350815     344970     302702     313910     334270     399504     414243
 3 ELEC.GEN.ALL-… 2021-04-01    NA         NA         NA     350815     344970     302702     313910     334270     399504
 4 ELEC.GEN.ALL-… 2021-05-01    NA         NA         NA         NA     350815     344970     302702     313910     334270
 5 ELEC.GEN.ALL-… 2021-06-01    NA         NA         NA         NA         NA     350815     344970     302702     313910
 6 ELEC.GEN.ALL-… 2021-07-01    NA         NA         NA         NA         NA         NA     350815     344970     302702
 7 ELEC.GEN.ALL-… 2021-08-01    NA         NA         NA         NA         NA         NA         NA     350815     344970
 8 ELEC.GEN.ALL-… 2021-09-01    NA         NA         NA         NA         NA         NA         NA         NA     350815
 9 ELEC.GEN.ALL-… 2021-10-01    NA         NA         NA         NA         NA         NA         NA         NA         NA
10 ELEC.GEN.ALL-… 2021-11-01    NA         NA         NA         NA         NA         NA         NA         NA         NA
# … with 422 more rows, and 16 more variables: value_lag9 <dbl>, value_lag10 <dbl>, value_lag11 <dbl>, value_lag12 <dbl>,
#   value_lag13 <dbl>, value_lag14 <dbl>, value_lag15 <dbl>, value_lag16 <dbl>, value_lag17 <dbl>, value_lag18 <dbl>,
#   value_lag19 <dbl>, value_lag20 <dbl>, value_lag21 <dbl>, value_lag22 <dbl>, value_lag23 <dbl>, value_lag24 <dbl>
>
```

modeltime::recursive()

Handles the iterative updating of lags with predictions.


```
> data_future_tbl %>% select(source_key, date, value, starts_with("value_lag"))
# A tibble: 432 x 27
   source_key     date       value value_lag1 value_lag2 value_lag3 value_lag4 value_lag5 value_lag6 value_lag7 value_lag8
   <chr>          <date>     <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>
 1 ELEC.GEN.ALL-… 2021-02-01    NA     350815     344970     302702     313910     334270     399504     414243     352766
 2 ELEC.GEN.ALL-… 2021-03-01    NA         NA     350815     344970     302702     313910     334270     399504     414243
 3 ELEC.GEN.ALL-… 2021-04-01    NA         NA         NA     350815     344970     302702     313910     334270     399504
 4 ELEC.GEN.ALL-… 2021-05-01    NA         NA         NA         NA     350815     344970     302702     313910     334270
 5 ELEC.GEN.ALL-… 2021-06-01    NA         NA         NA         NA         NA     350815     344970     302702     313910
 6 ELEC.GEN.ALL-… 2021-07-01    NA         NA         NA         NA         NA         NA     350815     344970     302702
 7 ELEC.GEN.ALL-… 2021-08-01    NA         NA         NA         NA         NA         NA         NA     350815     344970
 8 ELEC.GEN.ALL-… 2021-09-01    NA         NA         NA         NA         NA         NA         NA         NA     350815
 9 ELEC.GEN.ALL-… 2021-10-01    NA         NA         NA         NA         NA         NA         NA         NA         NA
10 ELEC.GEN.ALL-… 2021-11-01    NA         NA         NA         NA         NA         NA         NA         NA         NA
# … with 422 more rows, and 16 more variables: value_lag9 <dbl>, value_lag10 <dbl>, value_lag11 <dbl>, value_lag12 <dbl>,
#   value_lag13 <dbl>, value_lag14 <dbl>, value_lag15 <dbl>, value_lag16 <dbl>, value_lag17 <dbl>, value_lag18 <dbl>,
#   value_lag19 <dbl>, value_lag20 <dbl>, value_lag21 <dbl>, value_lag22 <dbl>, value_lag23 <dbl>, value_lag24 <dbl>
>
```

Part V

Scalability

3-Pro Tips

When dealing with **large scale.**

Pro-Tip 1: Start with 1 Time Series

Forecasting 1000's of time series is hard.

- Many Time Series
- Many Models

Simplify your problem.

Pro-Tip 2: Scale Efficiently

Time is your greatest resource. Use it wisely.

Strategy:

- **Test Many Models.** Hurts Time, Increases Accuracy
- **Parallel Processing.** Helps Time.

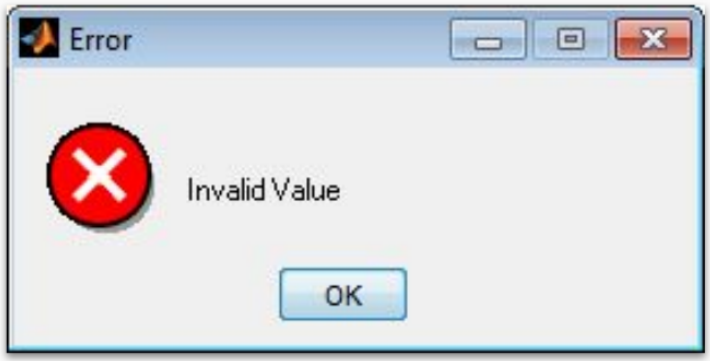
Pro-Tip 3: Anticipate errors.

People don't plan to fail. They fail to plan.

Anticipate that something will go wrong.

Have a plan.

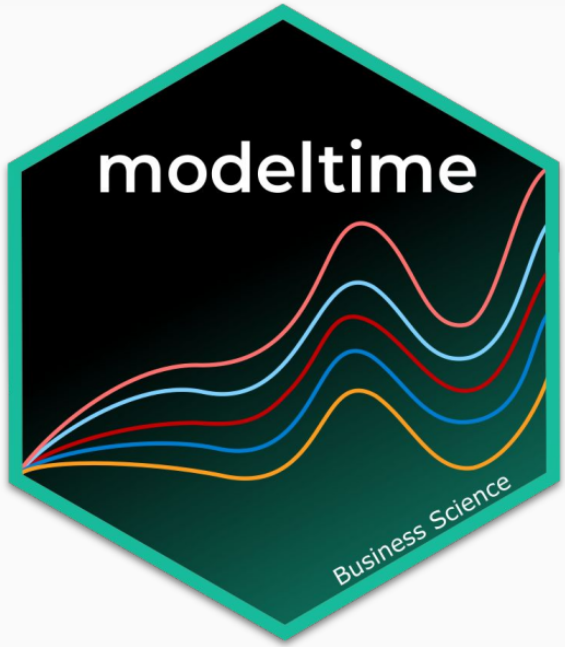
- Implement error reports
- Review all errors



Developed for Scale

We have 2 Systems to Scale:

1. **Global Modeling**: 100X faster
2. **Nested Modeling**: Slower, More Accurate




Global Model
GLMNET, XGBoost, SVM
Time Series 1
Time Series 2
...
Time Series N

Global Models

Customer ID	Date	Revenue	Event 1
1	2021-01-01	0	New Years Day
1	2021-01-02	400	
1	2021-01-03	250	
1	2021-01-04	300	
...	...	...	...
1000	2021-01-01	100	New Years Day
1000	2021-01-02	2050	
1000	2021-01-03	3575	
1000	2021-01-04	4035	

1000 Time Series

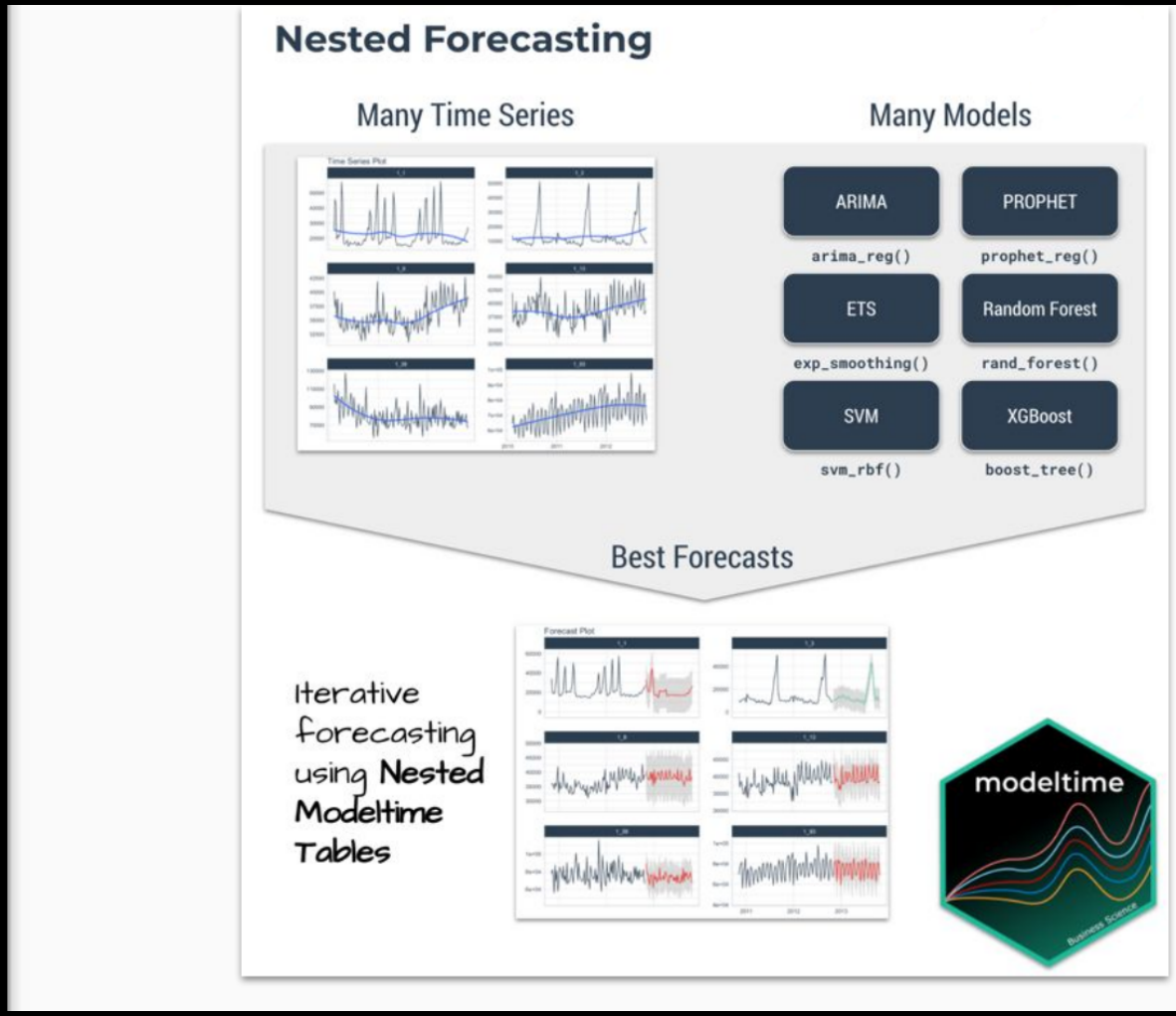
DeepAR 1

1 Global Model

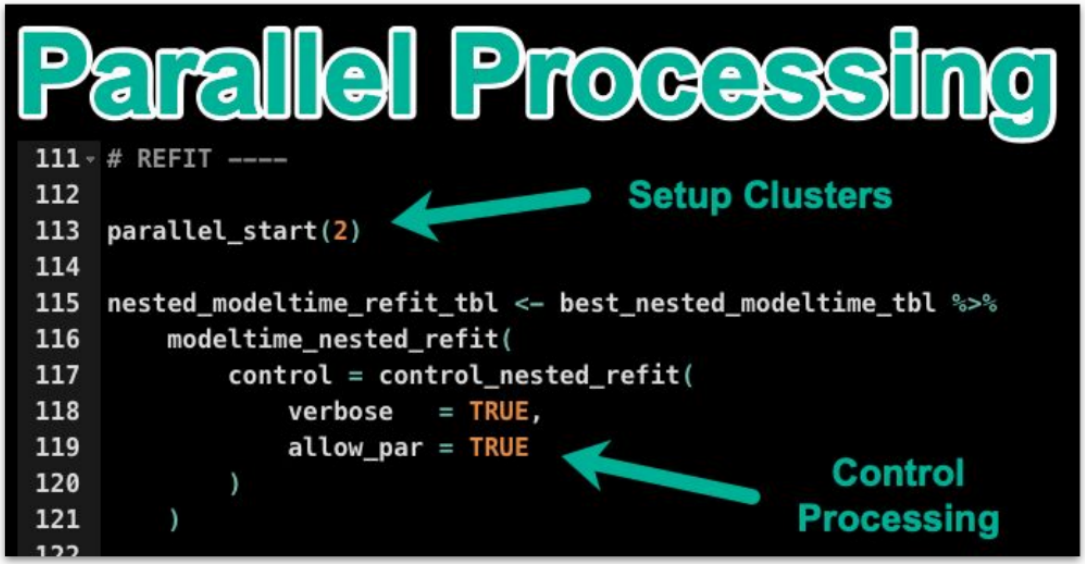
1000 Forecasts

Nested Forecasting

- Iterative Analysis
- Built for Scale (Parallel Processing)
- Handles Errors Gracefully
- Key Concepts: Logging



Extremely easy to run in parallel.

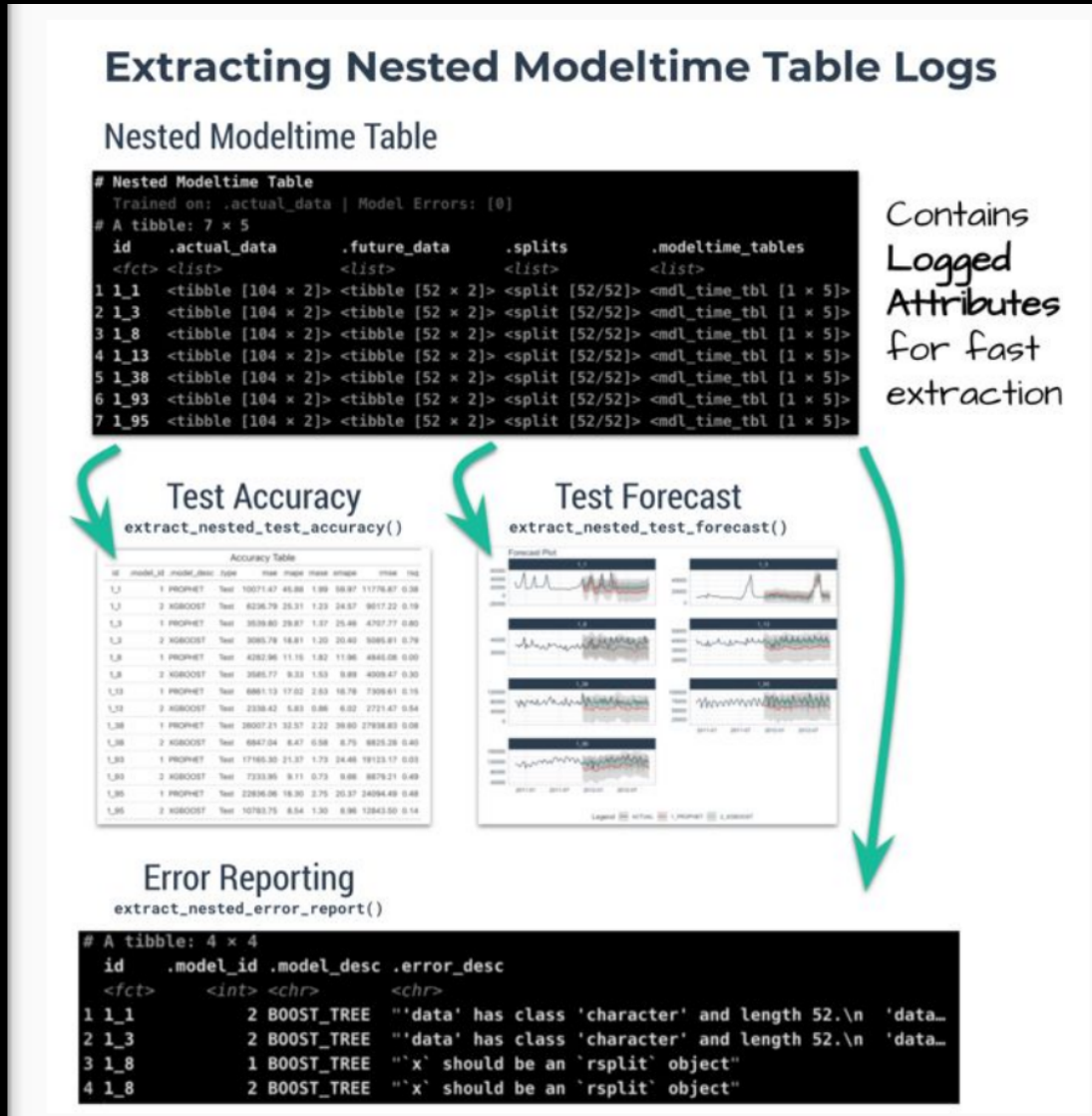


Logging & Error Handling

Pushes **everything** you need to the most expensive operation. Proceeds even when errors occur.

Benefit 1: Can retrieve key information instantly.

Benefit 2: Can check error logs & isolate edge cases where your analysis fails



Thank you!