The Biennial Medicaid Model

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Agenda

Model Context and the Big Picture

General Approach

Data

- Overview
- Percent Completion Factor

Modeling

- Method Overview
- Models Implemented
- Example Output

Power BI and Forecast Visualization

What?

- Model used by LFD to forecast biennial (short-term) Medicaid expenditures

Why?

- Serves as the Legislative Branch check on the Medicaid budget request brought forward by DPHHS every biennium

When?

- During session, Subcommittee B reviews estimates in January and an updated version in February

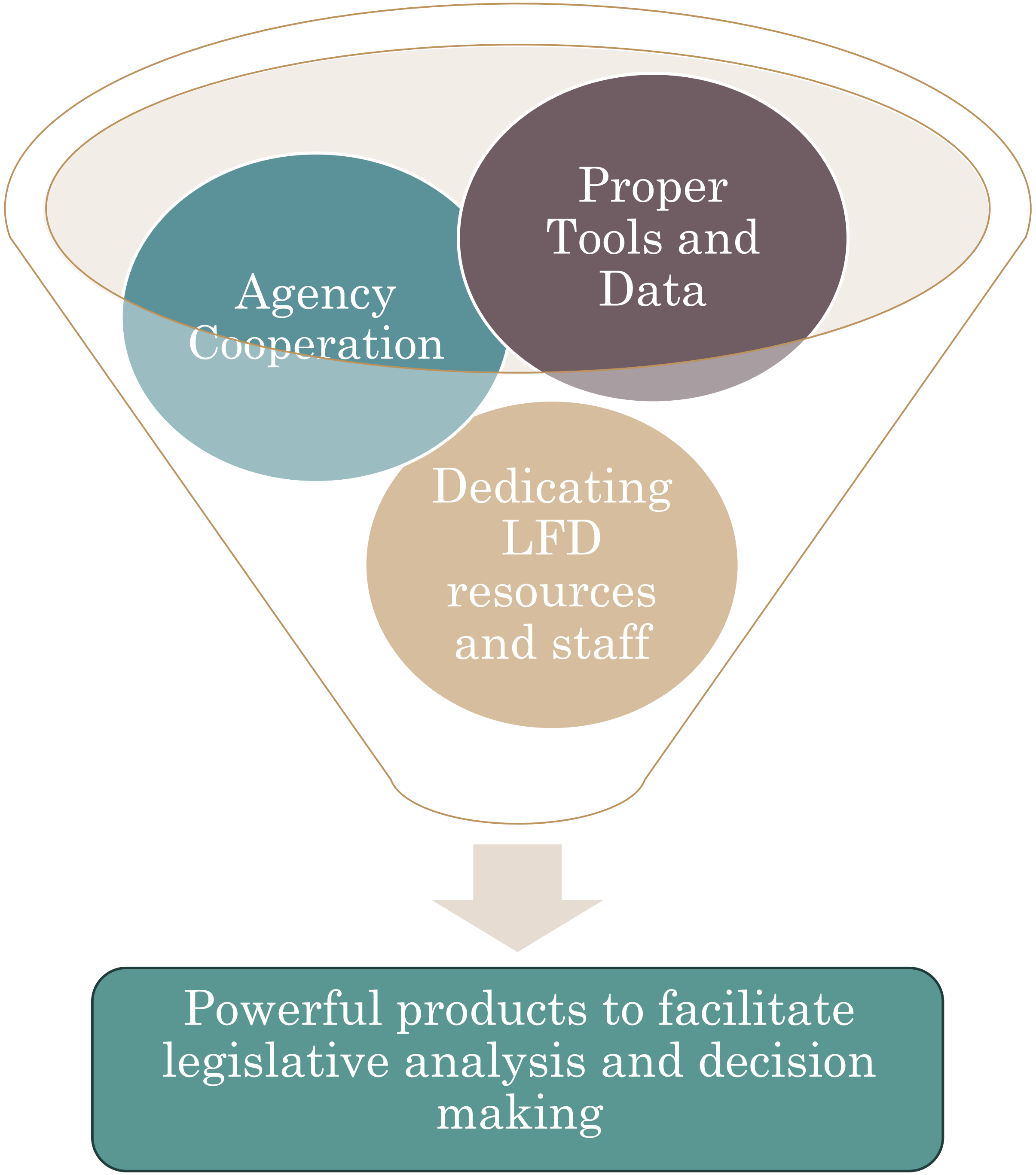
2013 LFD Biennial Medicaid Model

- Did not include Medicaid Expansion
- Over 5,000 lines of code and manual adjustments required
- ARIMA model implemented throughout

Current Capabilities

- Includes Medicaid Expansion
- Flexibility when new providers are added
- Tightened up the percent completion factor
- Quality of life improvements
  - ~30% of the previous model length
  - Zero manual inputs and automated wherever possible
  - Prioritized readability
  - Steps documented throughout
  - Fails gracefully
  - Significantly less processing time for significantly more computations
- Exogenous predictors
- Multiple different models implemented
- Model selection based on best fit

The Big Picture



General Approach

Data Driven

- Historical expenditures
- Macro-economic inputs

Method Driven

- Various robust methodologies implemented
- Method chosen by best-fit metrics

Quality Driven

- Flexible
- Automated
- Quick
- Well visualized output

Data

- 901 Report provider reimbursement data
  - Monthly data aggregated into quarterly values
  - As early as 2004 (dependent on provider type)
  - Pulled monthly
  - 200 separate provider types
- SABHRs monthly subclass data for non-901 provider types
  - Monthly data aggregated into yearly values
- Macroeconomic variables brought in through S & P Global
  - Quarterly frequency
  - Actuals and projections

The Challenge of Incomplete Data

Solution: A "**Percent Completion Factor**" that allows us to make informed estimates for recent years, even with partial information.

1. Compare historical data at different points in time
2. Calculate completion percentages for each past fiscal year
3. Find the median of those percentages
4. Apply this median percent to the most recent reporting data

Modeling

ModelTime

- Builds on the well established tidymodels ecosystem
- Brings together classic time series functionality, machine learning and deep learning
- Model chosen using best fit metrics
- Allows for different structures to forecast at scale
  - Global Modeling
  - Nested (or Iterative) Modeling

Common Model Structure

Develop a standard template for each type of model that prepares the data in the right format for analysis.

Specify a blueprint for the model including necessary engines and hyperparameters to ensure analysis is optimized.

Bring those two elements into a common workflow that is then performed iteratively on each time series.

Models Implemented

ARIMA (Baseline)

Exponential Smoothing

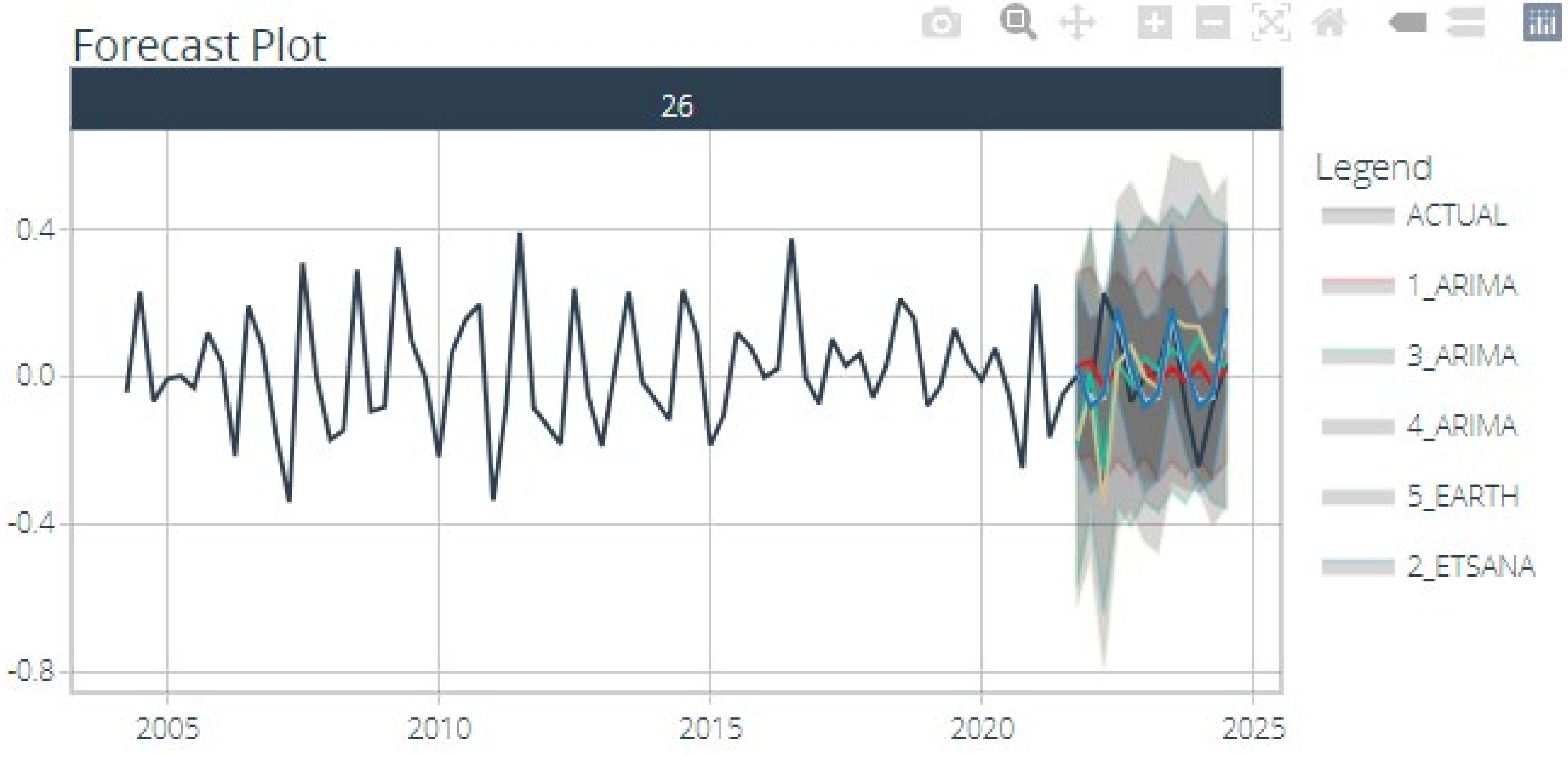
Arima with XGBoost

Multivariate Adaptive Regression Spline

Croston Exponential Smoothing

Example Forecast: Training

HRD – Audiologist



Provider_Index	26

Accuracy table with metrics

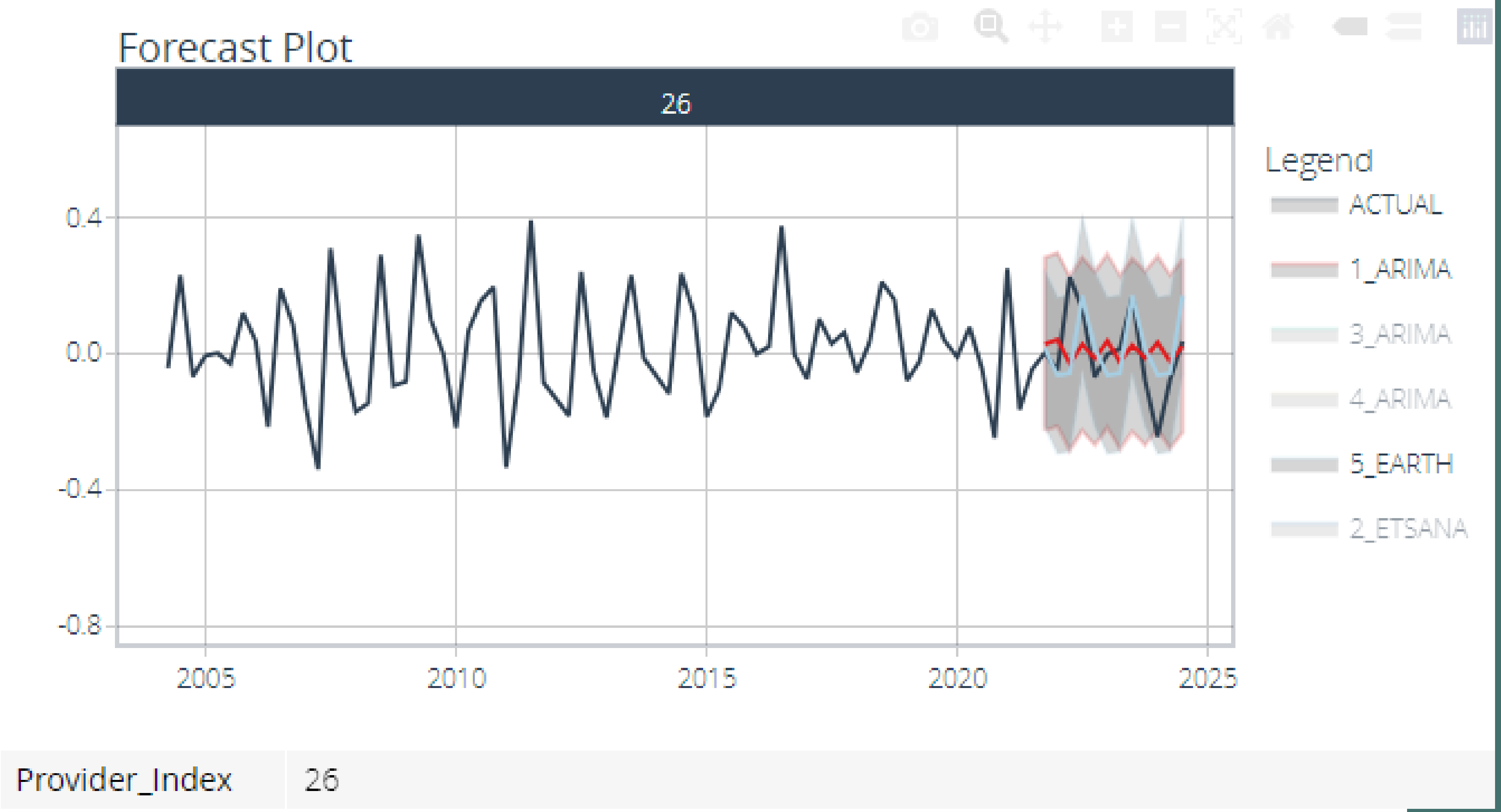
HRD – Audiologist

Provider_Index	.model_id	.model_desc	.type	mae	mape	mase	smape	rmse	rsq
26	1	ARIMA	Test	0.1	350.45	0.69	156.07	0.13	0.02
26	2	ETSANA	Test	0.09	582.12	0.65	128.51	0.12	0.24
26	3	ARIMA	Test	0.13	952.59	0.96	144.91	0.19	0.23
26	4	ARIMA	Test	0.15	736.09	1.08	137.49	0.22	0.23
26	5	EARTH	Test	0.08	432.53	0.59	121.85	0.11	0.21
26	6	NULL							

*currently model selection is based off the root mean squared error metric

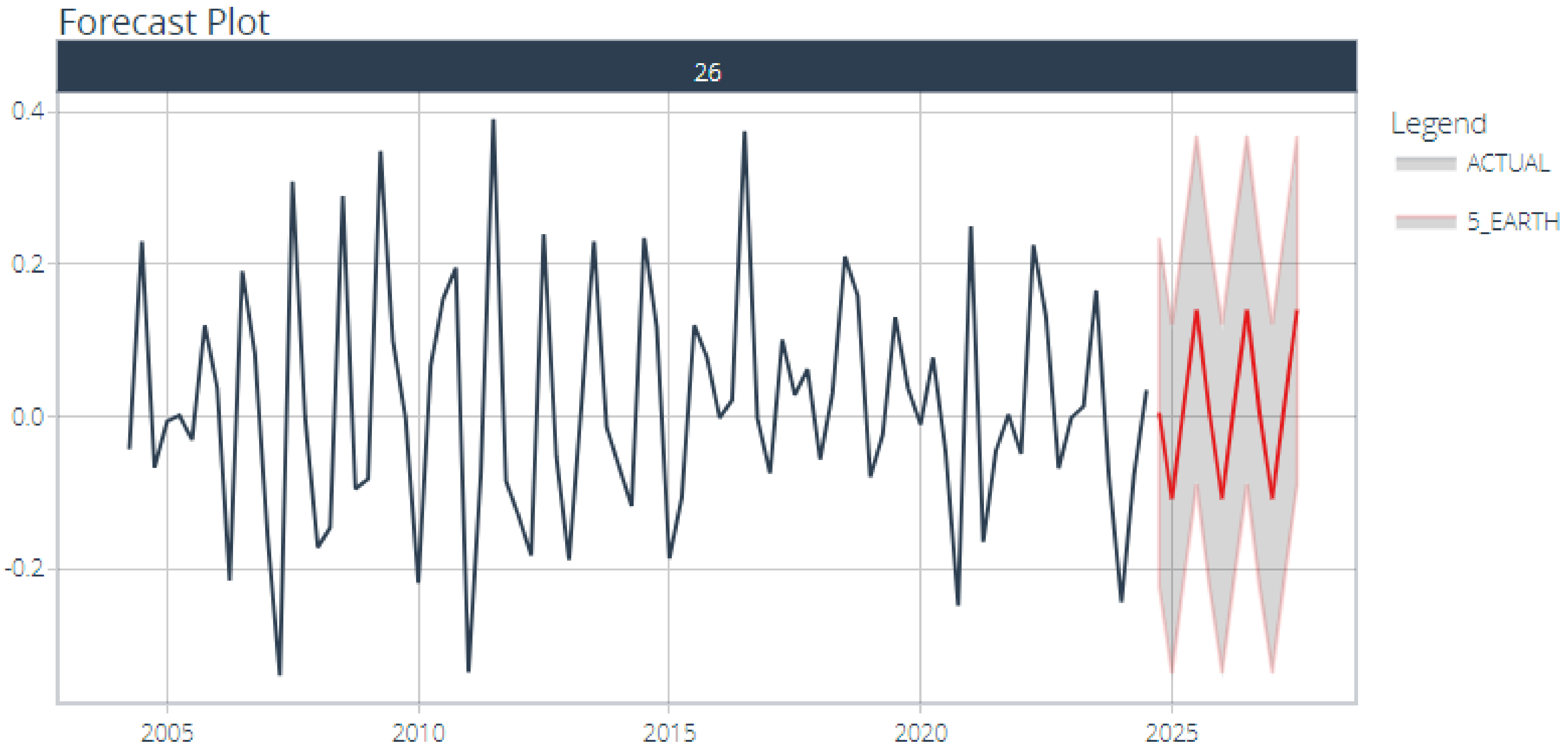
Best Fit Model Comparison
HRD – Audiologist

- RMSE –
  - ARIMA = 0.13
  - EARTH = 0.11
- RSQ –
  - ARIMA = 0.02
  - EARTH = 0.21



Example Forecast: Testing

HRD – Audiologist



Provider_Index	26

Power Bi Integration

Questions?

Sources

- Dancho M (2024). *modeltime: The Tidymodels Extension for Time Series Modeling*. R package version 1.3.0, https://business-science.github.io/modeltime/, https://github.com/business-science/modeltime.
- Hyndman, R.J., & Athanasopoulos, G. (2018) Forecasting: principles and practice, 2nd edition, OTexts: Melbourne, Australia. OTexts.com/fpp2.
- Kuhn M, Wickham H (2020). *Tidymodels: a collection of packages for modeling and machine learning using tidyverse principles.*. https://www.tidymodels.org.
- OpenAI. (2024). ChatGPT [Large language model]. https://chat.openai.com

Appendix A: Background Information

R Software

- Open-source software that can be extended via *packages*
- A language and environment for
    - *Data handling, storage and analysis*
    - *Statistical Computation*
    - *Looping, conditional, and user-defined recursive functions*
    - *Graphical Display*

- For more information visit the R-Project Website

Accuracy Metrics

- Root Mean Squared Error (RMSE) – measures the average difference between values predicted by a model and the actual values. Minimize. Due to squaring the difference, a few large differences will increase RMSE to a greater degree than other metrics.

$$\sqrt{\frac{1}{T}\sum_{i=1}^{T}(y_t - \hat{y}_t)^2}$$

- Mean Absolute Error (MAE) – calculated as the sum of absolute errors divided by the sample size. Minimize. Scale dependent. Conceptually simpler than RMSE

$$\frac{1}{T}\sum_{i=1}^{T}|y_t - \hat{y}_t|$$

- Mean Absolute Percentage Error (MAPE) – average percent difference from the true value. Various issues and not a good choice.

$$100 * \frac{1}{T}\sum_{i=1}^{T}\left|\frac{y_t - \hat{y}_t}{y_t}\right|$$

- Mean Absolute Scaled Error (MASE) – calculates the mean absolute error of the forecast values, divided by the mean absolute error of the in-sample one step naïve forecast.

$$\frac{\frac{1}{j}\sum_j |y_t - \hat{y}_t|}{\frac{1}{T-1}\sum_{t=2}^{T} |y_t - y_{t-1}|}$$

$$Naive\ Method: \hat{y}_{T+h|T} = y_t$$

- Symmetric Mean Absolute Percentage Error (SMAPE) – measure based on percentage (or relative) errors.

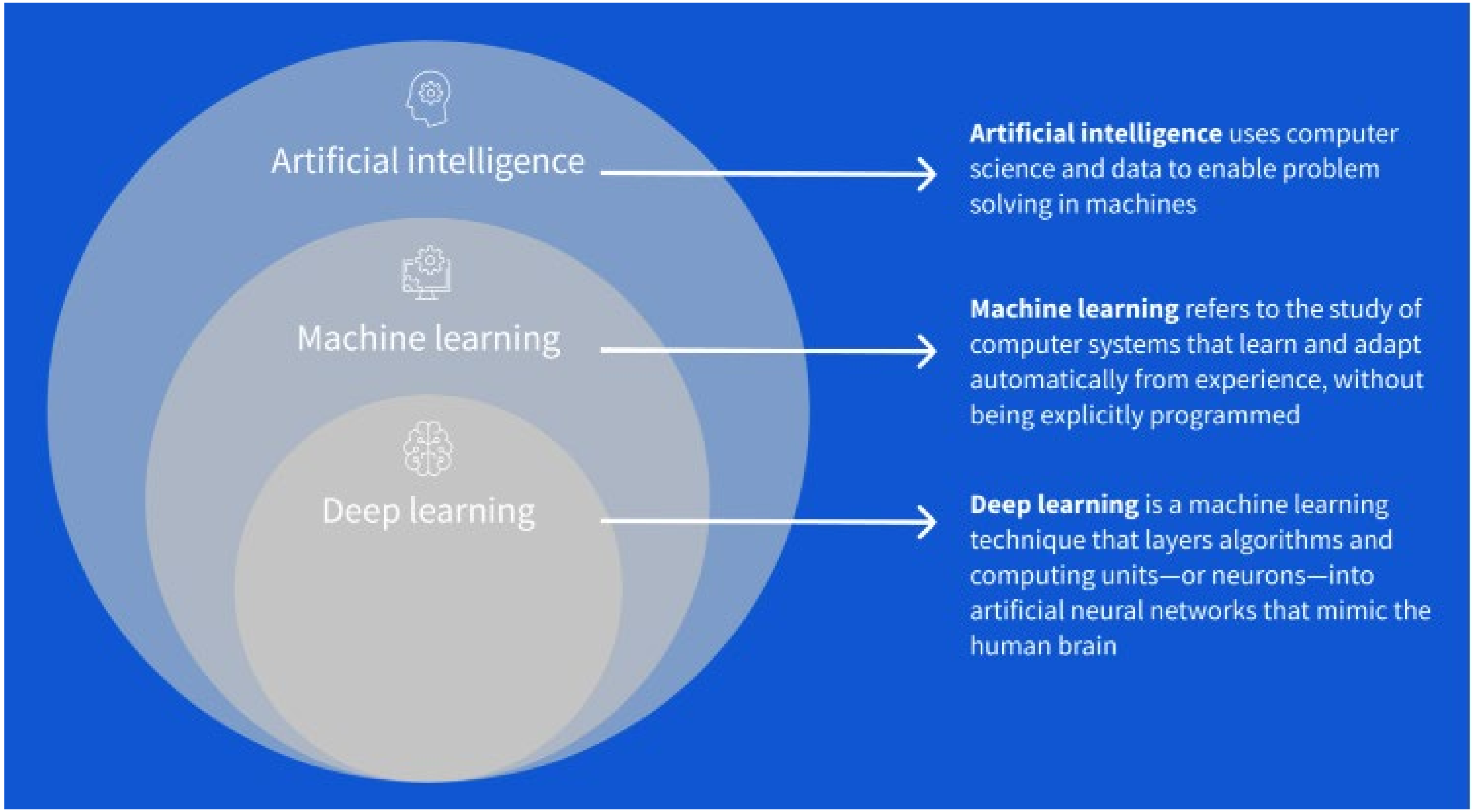
$$\frac{100}{n}\sum_{i=1}^{T}\frac{|y_t - \hat{y}_t|}{(|y_t| + |\hat{y}_t|)2}$$

- Coefficient of Determination (RSQ) – the proportion of the variation in the dependent variable that is predictable from the independent variables. Calculated as 1 minus the sum of squared residuals over the total sum of squares.

$$1 - \frac{\sum_{i=1}^{T}(y_t - \hat{y}_t)^2}{\sum_{i=1}^{T}(y_t - \bar{y}_t)^2} \text{ where } \bar{y}\ is\ the\ mean\ of\ the\ observed\ data$$

A baseline model, which always predicts $\bar{y}$ will have $R^2 = 0$. Models with a worse prediction than this baseline will have a negative R^2.

Machine Learning Vs. Deep Learning



* https://www.coursera.org/articles/ai-vs-deep-learning-vs-machine-learning-beginners-guide

Machine learning	Deep learning
A subset of AI	A subset of machine learning
Can train on smaller data sets	Requires large amounts of data
Requires more human intervention to correct and learn	Learns on its own from environment and past mistakes
Shorter training and lower accuracy	Longer training and higher accuracy
Makes simple, linear correlations	Makes non-linear, complex correlations
Can train on a CPU (central processing unit)	Needs a specialized GPU (graphics processing unit) to train

* https://www.coursera.org/articles/ai-vs-deep-learning-vs-machine-learning-beginners-guide

Appendix B: Data

Data Set-up

- Master data set lives on Snowflake
  - Historical 901 data
  - Forecasting categories crosswalk
- New cleaning file with **zero** manual input
  - File is saved with a particular naming convention that allows for automatically pulling needed report month and report year information out of the file name within the R script
- Batch file structure
  - Pulls most recent cleaned data and then uploads it to the master data set in Snowflake
  - Moves the 901 report to an archived folder automatically
- SABHRS direct connection to R for non-901 categories

Percent Completion Factor (2013 Model)

- 901 reports contain layers of monthly data going back 2 fiscal years for each PT
- Saved only the fiscal year end reports (Report Month = June)

$$R_{(Service\ Year,\ Report\ Year)} = FYE\ Reimbursed\ Value\ indexed\ by\ Serv.FY\ and\ Rep.FY$$
$$MC_{(MC\ Report\ year = \ Service\ Year+2)} = Most\ Complete\ Reimbursed\ Value\ indexed\ by\ FY$$

Fiscal Year	Lag 1	Lag 2	Lag 3
2015	$R_{(2015,2015)}/MC_{2017}$	$R_{(2015,2016)}/MC_{2017}$	$R_{(2015,2017)}/MC_{2017}$
2016	$R_{(2016,2016)}/MC_{2018}$	$R_{(2016,2017)}/MC_{2018}$	$R_{(2016,2018)}/MC_{2018}$
2017	$R_{(2017,2017)}/MC_{2019}$	$R_{(2017,2018)}/MC_{2019}$	$R_{(2017,2018)}/MC_{2019}$
2018	$R_{(2018,2018)}/MC_{2020}$	$R_{(2018,2019)}/MC_{2020}$	$R_{(2018,2020)}/MC_{2020}$
PCF	$Median(Lag\ 1\ Values)$	$Median(Lag\ 2\ Values)$	$Median(Lag\ 3\ Values)$

- Issues: the detail and not dynamic as further data was added

Percent Completion Factor (Current)

- Use ALL historical 901 reports

	Months since Quarter Star		0	1	2	3	4	5	6	7	8	9	10	11	12	13-18	19-24	24+
		Lag	Lag_0	Lag_1	Lag_2	Lag_3	Lag_4	Lag_5	Lag_6	Lag_7	Lag_8	Lag_9	Lag_10	Lag_11	Lag_12	Lag_13	Lag_14	Lag_Complete
	FiscalDOS. Year	FiscalDOS. Quarter	Corresponding Report Month															
Report Month Corresponding to each lag	2014	1	2014-01-01	2014-02-01	2014-03-01	2014-04-01	2014-05-01	2014-06-01	2014-07-01	2014-08-01	2014-09-01	2014-10-01	2014-11-01	2014-12-01	2015-01-01	2015-07-01	2016-01-01	2016-02-01
	2014	2	2014-04-01	2014-05-01	2014-06-01	2014-07-01	2014-08-01	2014-09-01	2014-10-01	2014-11-01	2014-12-01	2015-01-01	2015-02-01	2015-03-01	2015-04-01	2015-10-01	2016-04-01	2016-05-01
	2014	3	2014-07-01	2014-08-01	2014-09-01	2014-10-01	2014-11-01	2014-12-01	2015-01-01	2015-02-01	2015-03-01	2015-04-01	2015-05-01	2015-06-01	2015-07-01	2016-01-01	2016-07-01	2016-08-01
	2014	4	2014-10-01	2014-11-01	2014-12-01	2015-01-01	2015-02-01	2015-03-01	2015-04-01	2015-05-01	2015-06-01	2015-07-01	2015-08-01	2015-09-01	2015-10-01	2016-04-01	2016-10-01	2016-11-01
Reimbursed amount at each respective lag - Provider Type A	2014	1	200	300	400	500	800	900	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
	2014	2	500	700	800	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
	2014	3	100	300	400	600	800	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
	2014	4	500	700	800	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
	2014	1	0.20	0.30	0.40	0.50	0.80	0.90	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2014	2	0.50	0.70	0.80	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2014	3	0.10	0.30	0.40	0.60	0.80	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2014	4	0.50	0.70	0.80	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2015	1	0.30	0.39	0.48	0.57	0.83	0.91	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2015	2	0.57	0.74	0.83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2015	3	0.22	0.39	0.48	0.65	0.83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2015	4	0.57	0.74	0.83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2016	1	0.26	0.35	0.44	0.53	0.81	0.91	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2016	2	0.53	0.72	0.81	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Percent Complete - Provider Type A	2016	3	0.16	0.35	0.44	0.63	0.81	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2016	4	0.53	0.72	0.81	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Percent Completion Factor - For Provider Type A		1	0.26	0.35	0.44	0.53	0.81	0.91	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		2	0.53	0.72	0.81	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		3	0.16	0.35	0.44	0.63	0.81	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		4	0.53	0.72	0.81	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Provider.Type	Service.Fiscal.Quart	Median.Pct_00	Median.Pct_01	Median.Pct_02	Median.Pct_03	Median.Pct_04	Median.Pct_05	Median.Pct_06	Median.Pct_07	Median.Pct_08
CASE MANAGEMENT - MENTAL HEALTH (PT60)	2	0.04133	0.35934	0.68102	0.94841	0.97464	0.98799	0.99378	0.99637	0.99753
CASE MANAGEMENT - MENTAL HEALTH (PT60)	3	0.04287	0.34627	0.65860	0.96858	0.97819	0.98697	0.99349	0.99515	0.99620
CASE MANAGEMENT - MENTAL HEALTH (PT60)	4	0.05378	0.38418	0.68823	0.97047	0.98760	0.99059	0.99301	0.99501	0.99673
CRITICAL ACCESS HOSPITAL (PT74)	1	0.04276	0.33038	0.64318	0.89303	0.93975	0.96394	0.97765	0.98191	0.98878
CRITICAL ACCESS HOSPITAL (PT74)	2	0.06947	0.36025	0.69323	0.90706	0.95836	0.97383	0.97489	0.98733	0.98983
CRITICAL ACCESS HOSPITAL (PT74)	3	0.03588	0.31543	0.64435	0.88202	0.94434	0.97364	0.98683	0.99321	0.99514
CRITICAL ACCESS HOSPITAL (PT74)	4	0.08040	0.40735	0.66007	0.89860	0.95697	0.98970	0.99266	0.99930	0.99930
FEDERALLY QUAL HEALTH CENTER (PT56)	1	0.11610	0.38633	0.69229	0.88965	0.93878	0.94679	0.95145	0.96238	0.96345
FEDERALLY QUAL HEALTH CENTER (PT56)	2	0.14096	0.40295	0.70561	0.80904	0.85814	0.87108	0.92282	0.97336	0.98397
FEDERALLY QUAL HEALTH CENTER (PT56)	3	0.10717	0.34021	0.68102	0.82550	0.92576	0.94517	0.95196	0.96145	0.98911
FEDERALLY QUAL HEALTH CENTER (PT56)	4	0.13194	0.45080	0.72833	0.91272	0.93591	0.96563	0.97369	0.98421	0.98947
HOSPITAL - INPATIENT (PT01)	1	0.04778	0.28993	0.56461	0.85490	0.93328	0.94955	0.97562	0.98348	0.98454
HOSPITAL - INPATIENT (PT01)	2	0.05608	0.31906	0.62151	0.87398	0.92048	0.95398	0.97403	0.97673	0.98332
HOSPITAL - INPATIENT (PT01)	3	0.04400	0.28151	0.59997	0.91895	0.96238	0.97740	0.98368	0.98612	0.99008
HOSPITAL - INPATIENT (PT01)	4	0.03363	0.28407	0.63142	0.91162	0.97498	0.97424	0.98173	0.99048	0.99298
HOSPITAL - OUTPATIENT (PT02)	1	0.04292	0.34588	0.61224	0.89473	0.94703	0.96006	0.97609	0.98330	0.99115
HOSPITAL - OUTPATIENT (PT02)	2	0.04966	0.32180	0.61012	0.88588	0.93797	0.96704	0.97618	0.98965	0.99040
HOSPITAL - OUTPATIENT (PT02)	3	0.05483	0.28549	0.58491	0.88549	0.92753	0.95476	0.96719	0.96489	0.98302

Moving to incomplete years:

FYE Estimated Reimbursed Value = $Lagged\ Data\ \ /\ Relevant\ Median.Pct$

Appendix C: Time Series Analysis

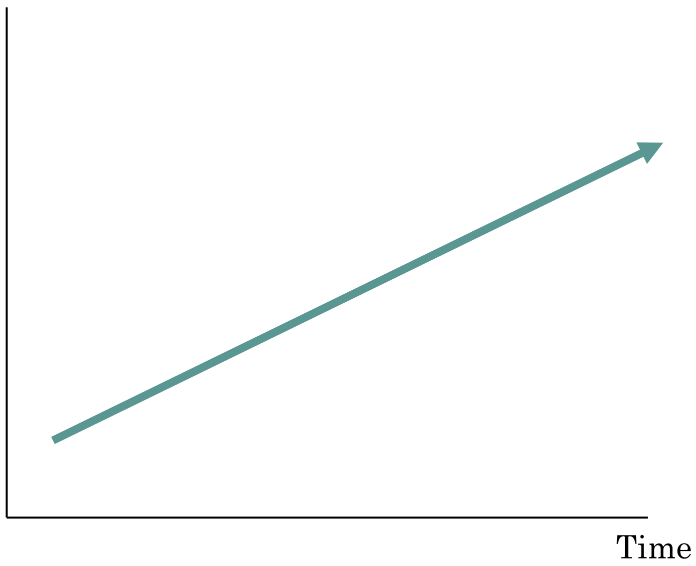
Time Series Model Components

Trend

– Captures the long term

– The general tendency of data to increase or decrease over time

– General medical inflation is captured under this component

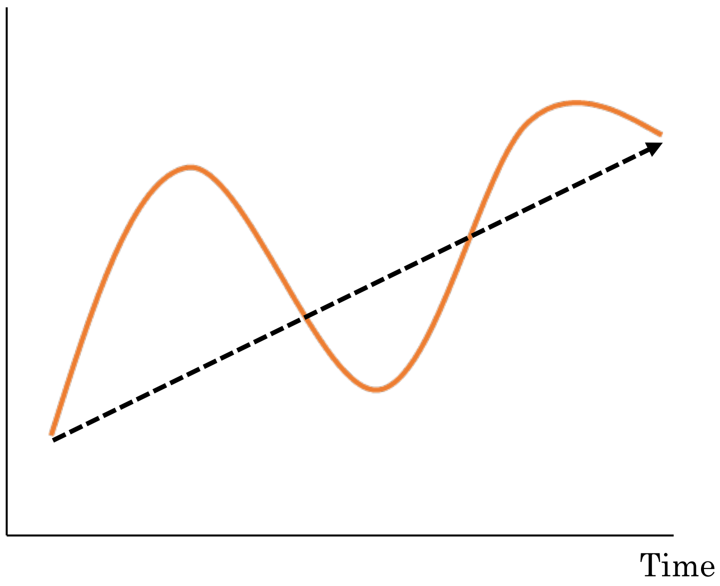


Long-term trend

Time Series Model Components

Cyclical Factors

- Medium-term cycles, generally over 2 or more years
- Captures the parts of the data which can be explained by other cyclical movements in the economy (i.e. unemployment)
- Can occur at any time of year; unpredictable



Long-term trend with cyclical variations

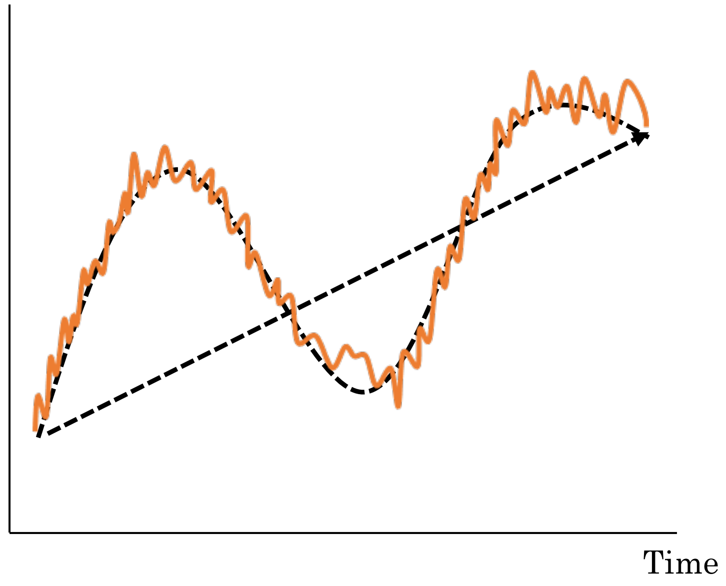
Time Series Model Components

Seasonality

– Captures short-term cycles

– The variation in a variable due to some predetermined patterns in its behavior; predictable

– Repetitive patterns that show up at certain times of the year (Ex: Increased hospital expenditures in the winter due to influenza)



Long-term trend with cyclical and seasonal variations

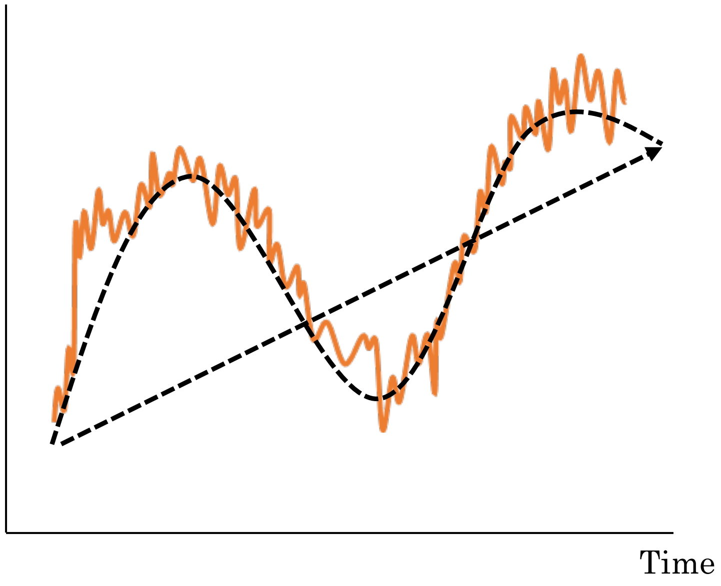
Time Series Model Components

- **Residual Variation**

– Unpredictable random influences outside of regular patterns; it basically captures everything left over after the other three components are isolated

– Also called random noise or random variation

– Cannot be replicated by repeating an experiment again



Long-term trend with cyclical, seasonal and residual variations

Key Modeling Assumption

- **Stationarity** must be satisfied.
- What does this mean?
  - A series whose properties do not depend on the time at which the series is observed.

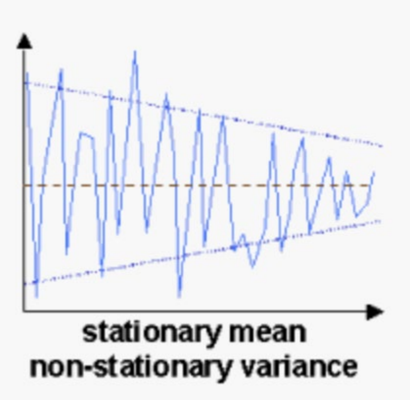
    Or
  - The time series must have no predictable patterns in the long term

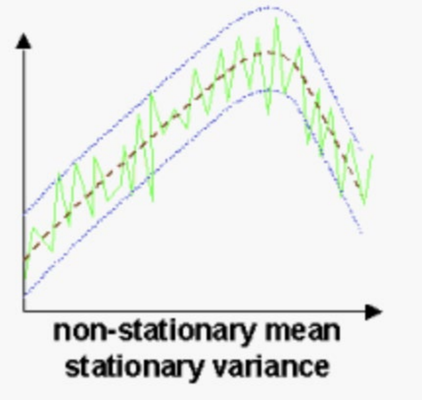
Mathematically, the mean, variance and autocovariance must remain constant over time

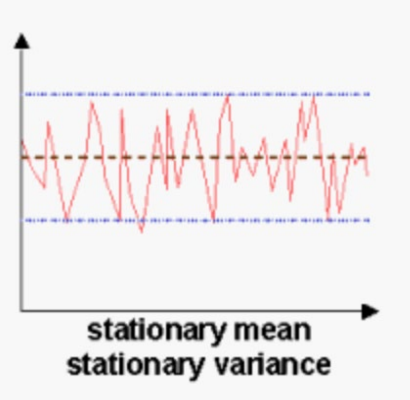
1. $E[y_t] = E[y_{t+k}]$
2. $var(y_t) = var(y_{t+k})$
3. $cov(y_t, y_{t+k}) = cov(y_{t+i}, y_{t+k+i})$

The Hurdle of Time Series Analysis at Scale

- Time Series need to fill certain basic assumptions
  - Weak Stationarity – constant mean, constant finite variance, minimal skew
- Manual Process: Transformed → metrics are taken → compared to original → repeat
- Types of Transformations
  - *Differencing
  - Seasonal Differencing
  - *Logarithmic
  - Power
  - *Sequences of multiple – i.e. Logarithmic then differencing
  - Box-Cox Transformation
- Metrics are used, but often visual analysis is an important part of that process
- We have over 200 time series to deal with over varying length and structure and limited time to do so







*https://towardsdatascience.com/stationarity-in-time-series-analysis-90c94f27322

The Solution

Transformation Selection Function

- Transformations are selected by weighted scores determined in part by stationarity, variance and skewness metrics

$$\textit{weighted score} = \mathrm{w}_{adf} * \left(\mathrm{min}_{adf} - \mathrm{value}_{i,adf}\right) + \mathrm{w}_{skew} * \left(\mathrm{min}_{skew} - \mathrm{value}_{i,skew}\right) + \mathrm{w}_{var} * \left(\mathrm{value}_{i,var} - \mathrm{max}_{var}\right)$$

- The lower the absolute value of the score, the better.
- The further the transformation's metric is from the best metric for that time series, the more it is penalized

Transformation Analysis Function: Solving for Weights

Variables

Stationarity Metric = $p_{adf,n}$

Variance Metric = $p_{tv,n}$

Skew metric = s_n

Stationarity Weight = w_{adf}

Variance Weight = $w_{tv} = 1$

Skew Weight = w_{skew}

Assumptions

$$w_{adf} > w_{tv} > w_{skew}$$

Optimal Metrics – $\min(p_{adf})$, $\max(p_{tv})$, $\min(s)$

$p_{adf,n}$ should be between (0.01 and 0.05) $\therefore \min p_{adf} - p_{adf,n} \leq .04$

Optimally, $p_{tv,n}$ is within .5 of the others $\therefore p_{tv} - max\, p_{tv} \leq .5$

$$s_2 - s_1 < 3$$
$$W_{score\ 1} < W_{score\ 1}$$
$$\min p_{adf} = p_{adf,1}$$
$$\max p_{tv} = p_{tv,2}$$
$$\min s = s_2$$

Fundamental Equation*

$$W_{score} = w_{adf}(\min p_{adf} - p_{adf,n}) + w_{tv}(p_{tv} - max\, p_{tv}) + w_{skew}(\min s - s_n)$$
$$w_{skew}(\min s - s_n)$$

*Best score is the minimum absolute value of the collection of weighted scores.

We care about the edge case. The problem we need to solve is where skew should make a difference.

$$W_{score\ 1} < W_{score\ 2}$$

$$p_{adf,1} < p_{adf,2} - .04 \xrightarrow{\text{yields}} p_{adf,1} - p_{adf,2} < -0.04$$

$$p_{tv,1} > p_{tv,2} - .5 \xrightarrow{\text{yields}} p_{tv,1} - p_{tv,2} > -0.5$$

$$s_2 < s_1$$

$$W_1 = w_{adf}(\min p_{adf} - p_{adf,1}) + w_{tv}(p_{tv,1} - \max p_{tv}) + w_{skew}(\min s - s_1)$$
$$W_2 = w_{adf}(\min p_{adf} - p_{adf,2}) + w_{tv}(p_{tv,2} - \max p_{tv}) + w_{skew}(\min s - s_2)$$

$$w_{adf}\cancel{(p_{adf,1} - p_{adf,1})} + 1\,(p_{tv,1} - p_{tv,2}) + w_{skew}(s_2 - s_1) < w_{adf}(p_{adf,1} - p_{adf,2}) + 1\,\cancel{(p_{tv,2} - p_{tv,2})} + \cancel{w_{skew}(s_2 - s_2)}$$

$$1\,(p_{tv,1} - p_{tv,2}) + w_{skew}(s_2 - s_1) < w_{adf}(p_{adf,1} - p_{adf,2})$$

$$1\,(-0.5) + w_{skew}(s_2 - s_1) < w_{adf}(-0.4)$$

Solution Equation: $-.5 + w_{skew}(s_2 - s_1) < w_{adf}(-0.4)$

$$s_2 - s_1 < 3$$
$$w_{adf} > w_{tv} > w_{skew}$$

$$12.5 + w_{skew}(-75) \quad < \quad w_{adf}$$

$$12.5 + w_{skew}\,(-75) > w_{tv} > w_{skew}$$

$$12.5 + w_{skew}\,(-75) > 1 > w_{skew}$$

$$12.5 + w_{skew}\,(-75) > 1$$

$$w_{skew}\,(-75) > \quad -11.5$$

$$\frac{w_{skew}\,(-75)}{-75} > \quad \frac{-11.5}{-75}$$

$$\boldsymbol{w_{skew} < \ .15\overline{3}}$$

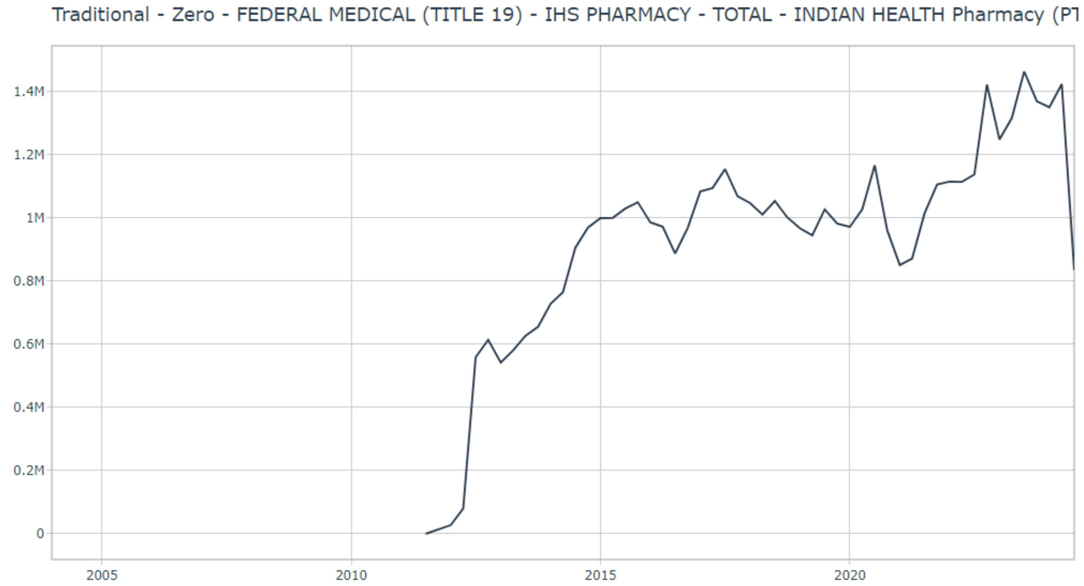
Types of Transformations

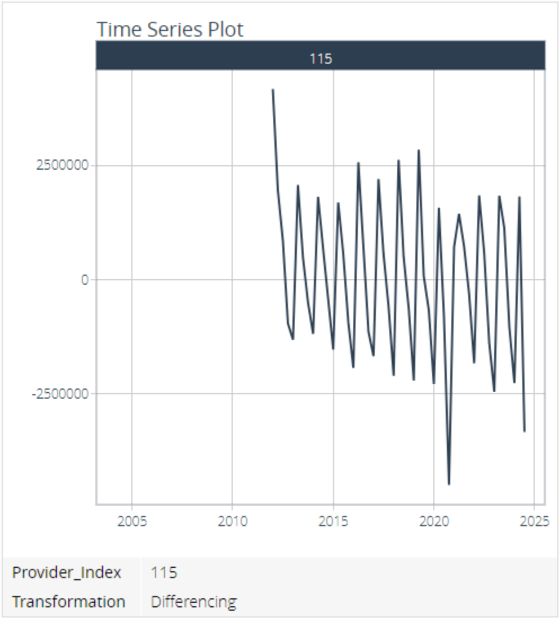
- Linear transformations are used to make data stationary
- Transformations used in our model:
  - Differencing

    $y'_t = y_t - y_{t-1}$
  - Logarithmic

    $y'_t = \log(y_t)$
  - Logarithmic differencing

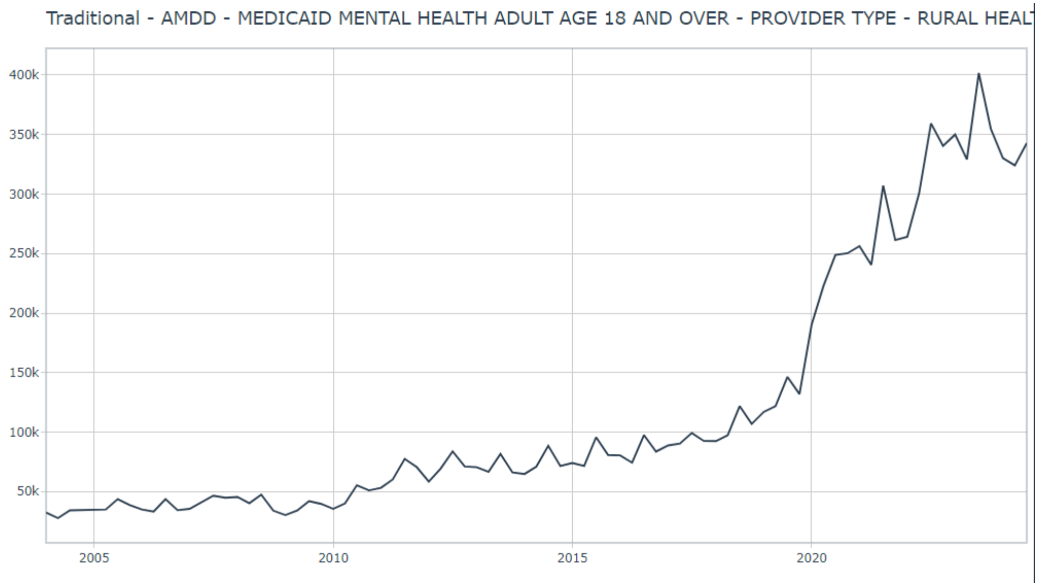
    $y'_t = \log(y_t) - \log(y_{t-1})$

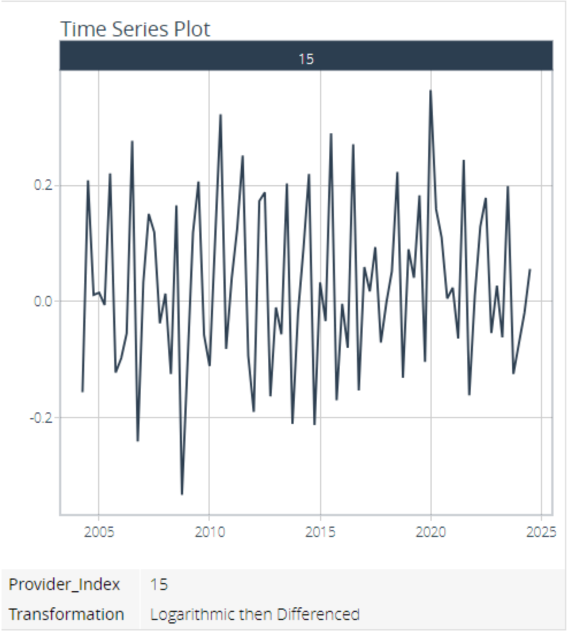




Original Data

Transformed Data





Provider_Index	.actual_data	.future_data	.splits
3	1 variable	1 variable	list(idx_train = 1
4	1 variable	1 variable	list(idx_train = 1
5	1 variable	1 variable	list(idx_train = 1
6	1 variable	1 variable	list(idx_train = 1
7	1 variable	1 variable	list(idx_train = 1
8	1 variable	1 variable	list(idx_train = 1
9	1 variable	1 variable	list(idx_train = 1
10	1 variable	1 variable	list(idx_train = 1
11	1 variable	1 variable	list(idx_train = 1
12	1 variable	1 variable	list(idx_train = 1
13	1 variable	1 variable	list(idx_train = 1
14	1 variable	1 variable	list(idx_train = 1
15	1 variable	1 variable	list(idx_train = 1

ModelTime: Nested Objects