

Modeling Claims and Economic Indicators

Data Science in Action

Actuaries Club of Hartford and Springfield

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Dental Dental of New Jersey and Connecticut

November 10, 2022



Agenda

- ▶ About us
- ▶ Strategy and business questions
- ▶ Data organization
- ▶ Modeling approach
- ▶ Business questions and analysis
- ▶ Next steps and recap



Delta Dental of New Jersey has been a market leader since 1969

- Offering the largest network of dental providers in New Jersey and Connecticut
- First organization to provide pre-paid dental benefits
- 1.9 million members covered

Delta Dental Plans Association

- 157,000+ groups, 85 million Americans covered
- Delta Dental covers 487 of Fortune 1000 companies

Nationwide plan with the advantage of local market relationships

- Localized network development and contracting
- One national provider file for consistent claims payments & discounts

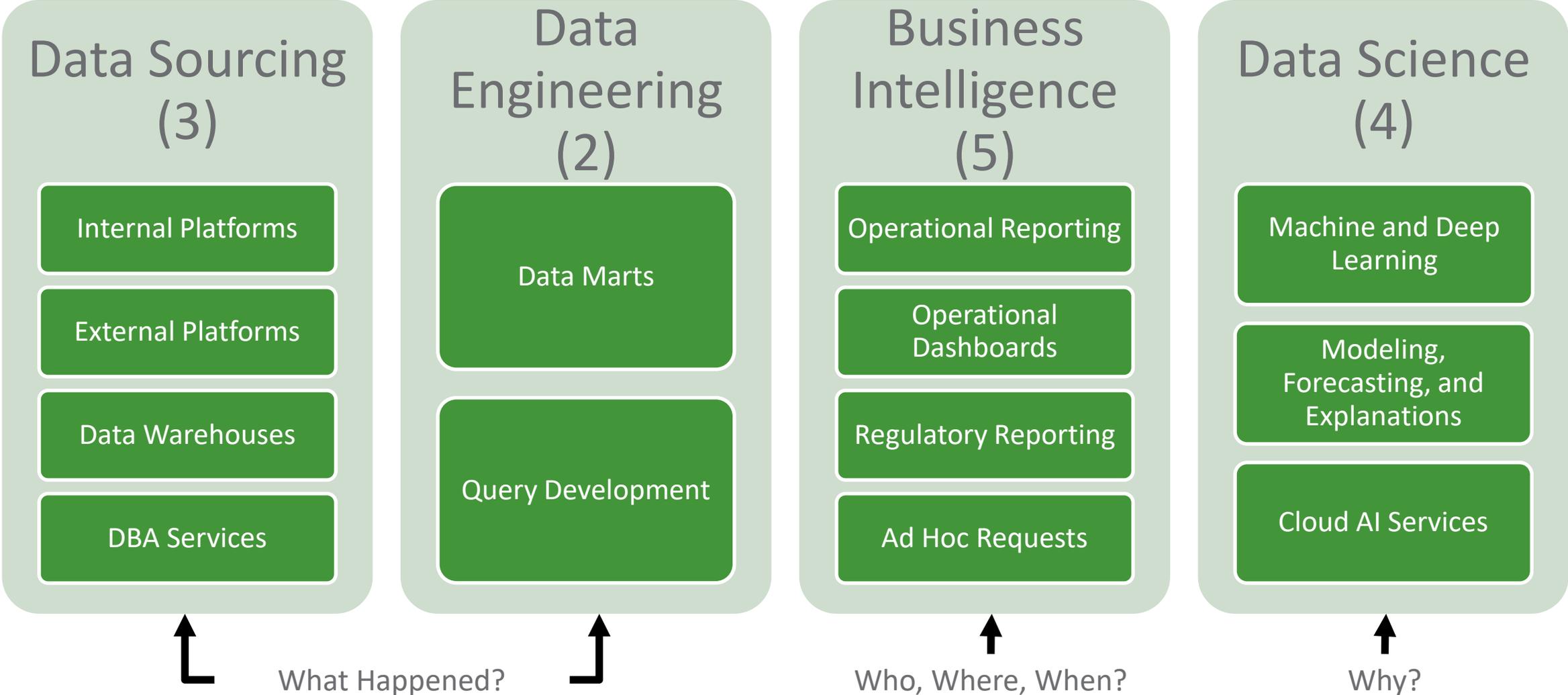
Long-term client relationships

- 98% of our clients would recommend Delta Dental to another benefits administrator



IT / Strategic Data Services and Decision Support

SDS Teams



Data Science Concepts

What we work with

Data
– forms, images, audio

Labels
– outcomes

Features
– what characterizes data

How – the methods

Unsupervised learning –
label afterwards

Supervised learning
– label first

Semi-supervised
– multiple grades of labels

Where are features identified

Machine Learning
– human selects features

Deep Learning
– neural network selects
features

“Look for precision, in each class of things, no further than the nature of the subject admits.”

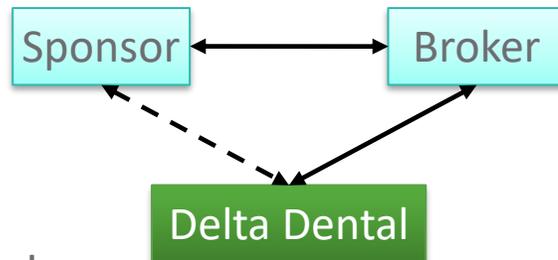
Aristotle, Nicomachean Ethics, ca 330 BCE

Strategy: Interactions – produce revenue, incur costs

We can think of our business as facilitating interactions among well defined groups. On the revenue side these are the people involved in buying the plans.

On the cost side these are the people involved in dental treatments; we need to model member and provider behaviors

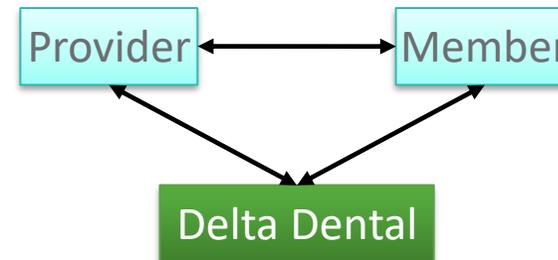
► Revenue – Sales and Marketing



► For Future ...

- Group and Individual business lines have different interaction structures
- Within a year revenue variability across comparable groups is much lower than claims payout variations.

► Costs - Operations



- Call Center
- Digital Platform
- IVR
- Claims
- Future: Chat, SMS, ...

What do we want to know about claims?

The Asks

- 1. Can we identify leading indicators for our business; especially for a recession/downturn?
- 2. Can we improve our end of year forecasting for the budget cycle; more accurate forecast and/or lower spread?
- 3. Can we improve estimates of the expected margin when underwriting a group?
- 4. Can we flag claims that are out of the ordinary (anomalies) for additional review?
- 5. Can we identify providers who are making unusual numbers or types of claims for restorations?



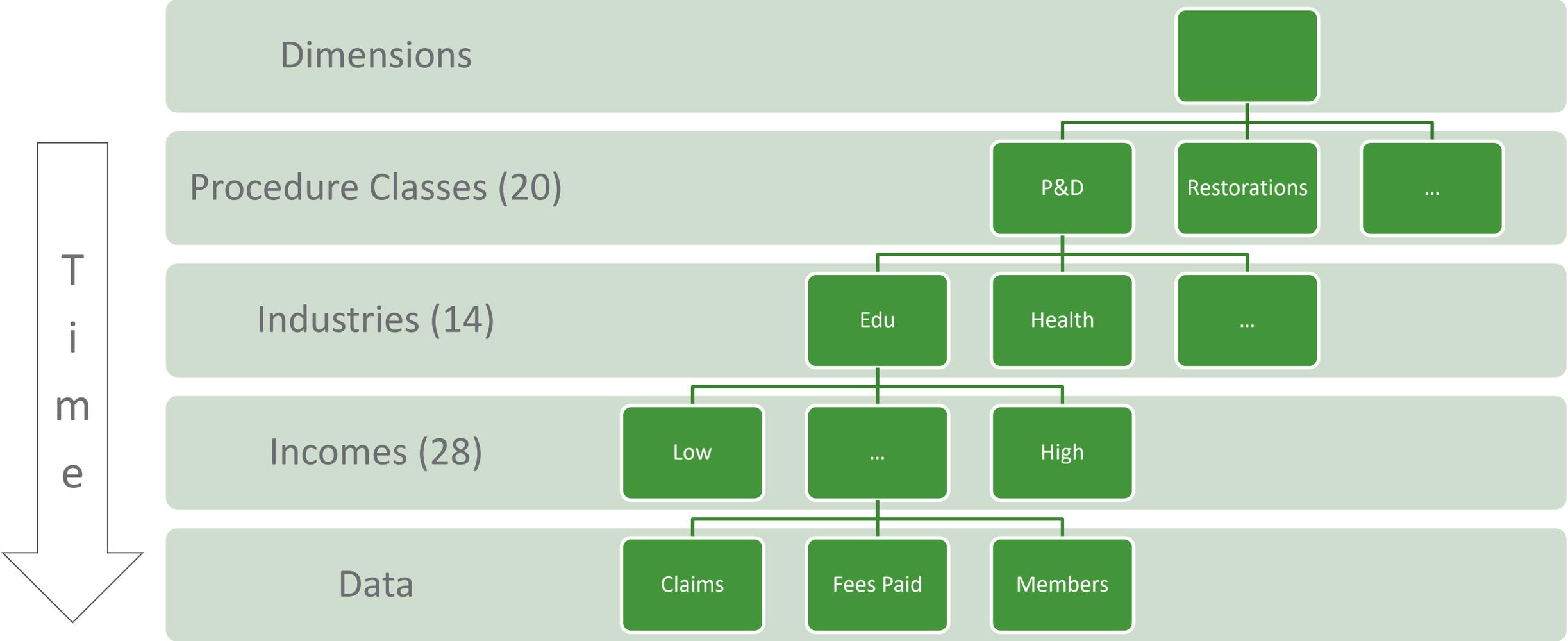
Modeling Member (patient) behavior

Modeling Provider (dentist) behavior



Time series dataset for claims analytics

Potentially 7,840 separate time series to model, then aggregate. Many series have little data, so we drop those.



Industry Sectors

We needed to compile a comprehensive view of DDNJ’s data that answers 4 main questions

▶ **When?**

- ▶ 2015 January through 2019 December, pre COVID
- ▶ 2015 January through 2022 October, include COVID

▶ **What?**

- ▶ Procedure Classes, primarily Preventive and Diagnostic and Restorative

▶ **Who?**

- ▶ Each claim line is associated with an NAICS Code
- ▶ At level 2 we have 28 NAICS codes
- ▶ Start with the 13 Industry Classification Sectors from the 2021 Census
- ▶ Split “Education and Health Services” into separate sectors to align with the DDNJ business
- ▶ Formed 14 DDNJ Industry Sectors

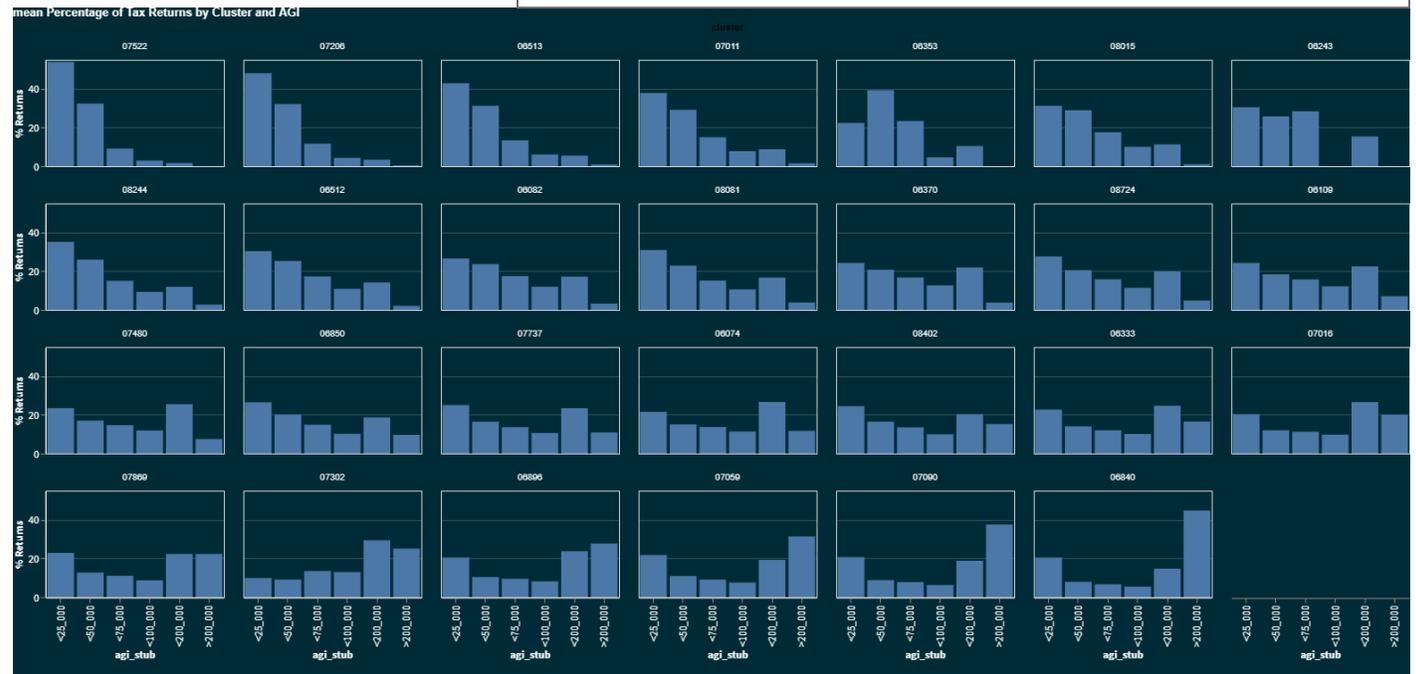
DDNJ Industry Sector	NAICS Level 2 Coding
Agriculture, forestry, fishing, and hunting	[11]
Construction	[23]
Education	[61]
Financial activities	[52, 53]
Health Services	[62]
Information	[51]
Leisure and Hospitality	[71, 72]
Manufacturing	[31, 32, 33]
Mining, quarrying, and oil and gas extraction	[21]
Other Services	[81]
Professional and Business Services	[54, 55, 56]
Public Administration	[92]
Transportation and utilities	[22, 48, 49]
Wholesale and retail trade	[42, 44, 45]

Where - Clustering Zip codes by Income

Hypothesis – localities with similar income profiles will have similar behaviors

- ▶ Used the IRS Individual Income Tax Zip Code Data
 - ▶ Provides 807 Zip Codes in NJ/CT along with an AGI distribution (six bands)
 - ▶ At least 500 tax returns aggregated in each zip code
 - ▶ Smaller zip codes (<500 returns) are merged into the nearest zip code. The impact is not great, ~3% of claims.
- ▶ Clustering using affinity propagation
- ▶ Produced 28 groupings
 - ▶ Between 1 and 65 zip codes in each cluster
 - ▶ Most clusters aggregate over 100,000 returns
 - ▶ Average AGI ranges from \$29,400 to \$537,000.
 - ▶ Grid is organized by average AGI lowest average AGI in top left, across and down to highest AGI in bottom right.

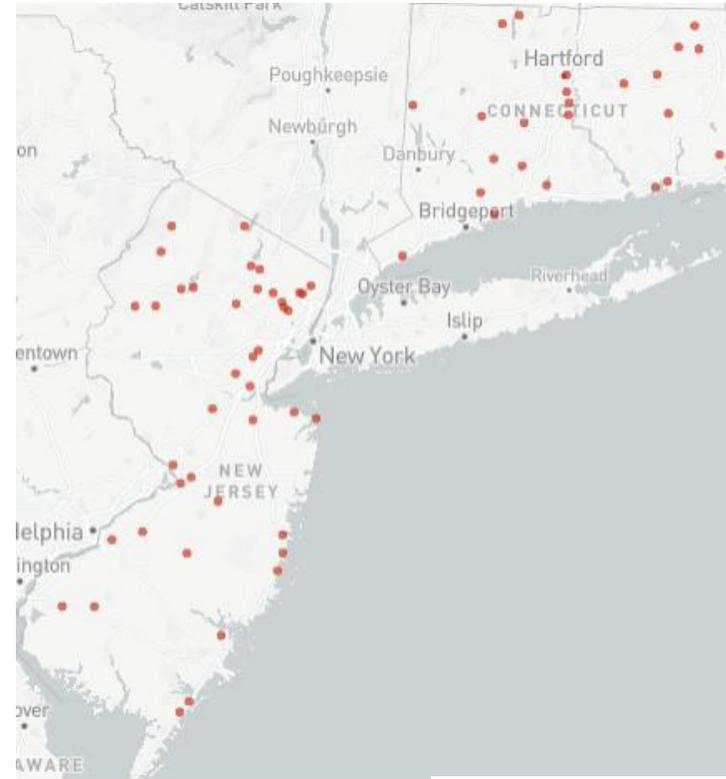
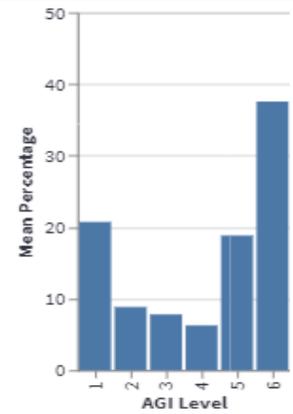
For each income cluster the plots show the percentage of returns in each AGI band



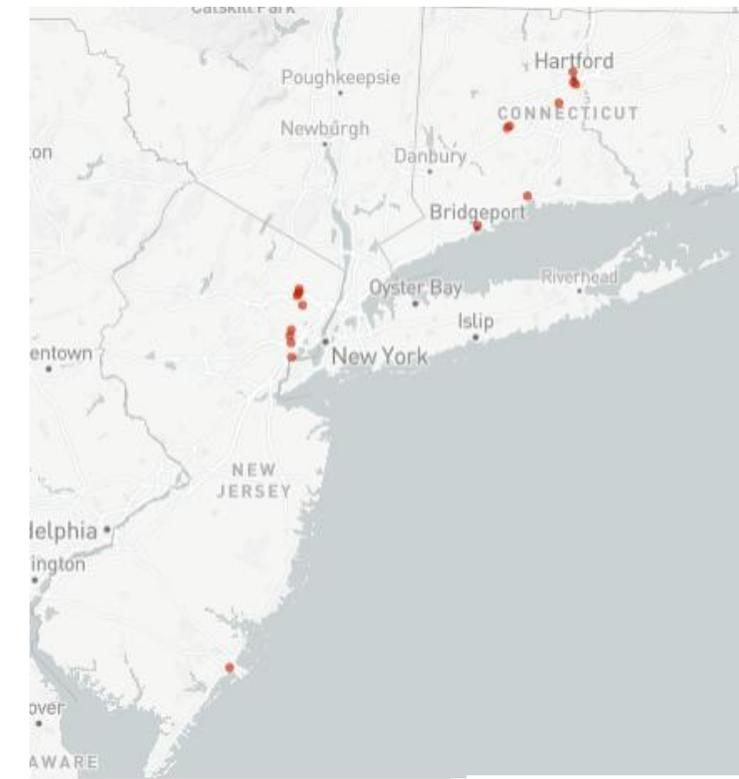
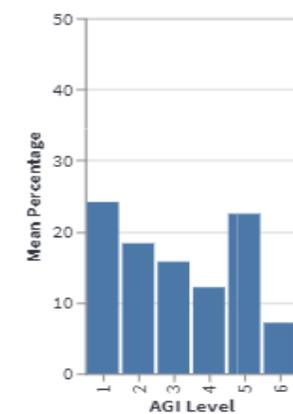
Where – Localities with similar Income profiles



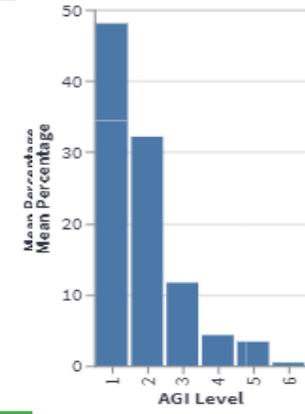
Cluster 07090
High Income
21 Zip Codes



Cluster 06109
Middle Income
65 Zip Codes
Used for
example slides



Cluster 07206
Low Income
18 Zip Codes



Modeling behaviors

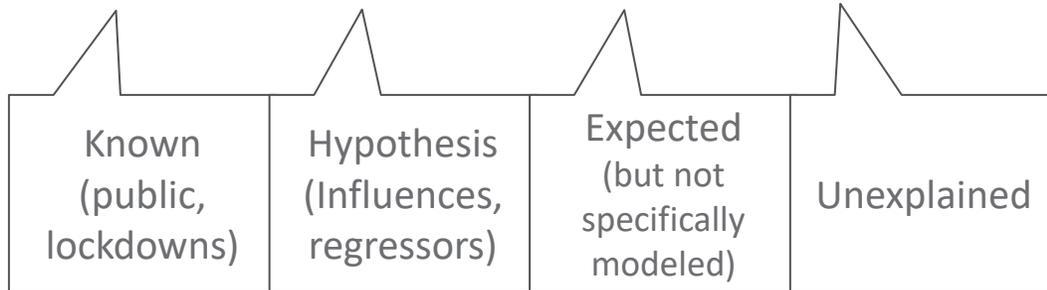
Descriptive models

Model = trend + seasonality + holidays + [externals] + noise

- ▶ These tell us what happened, may make good predictions but don't tell us why. A model may be fitted without any external predictors.

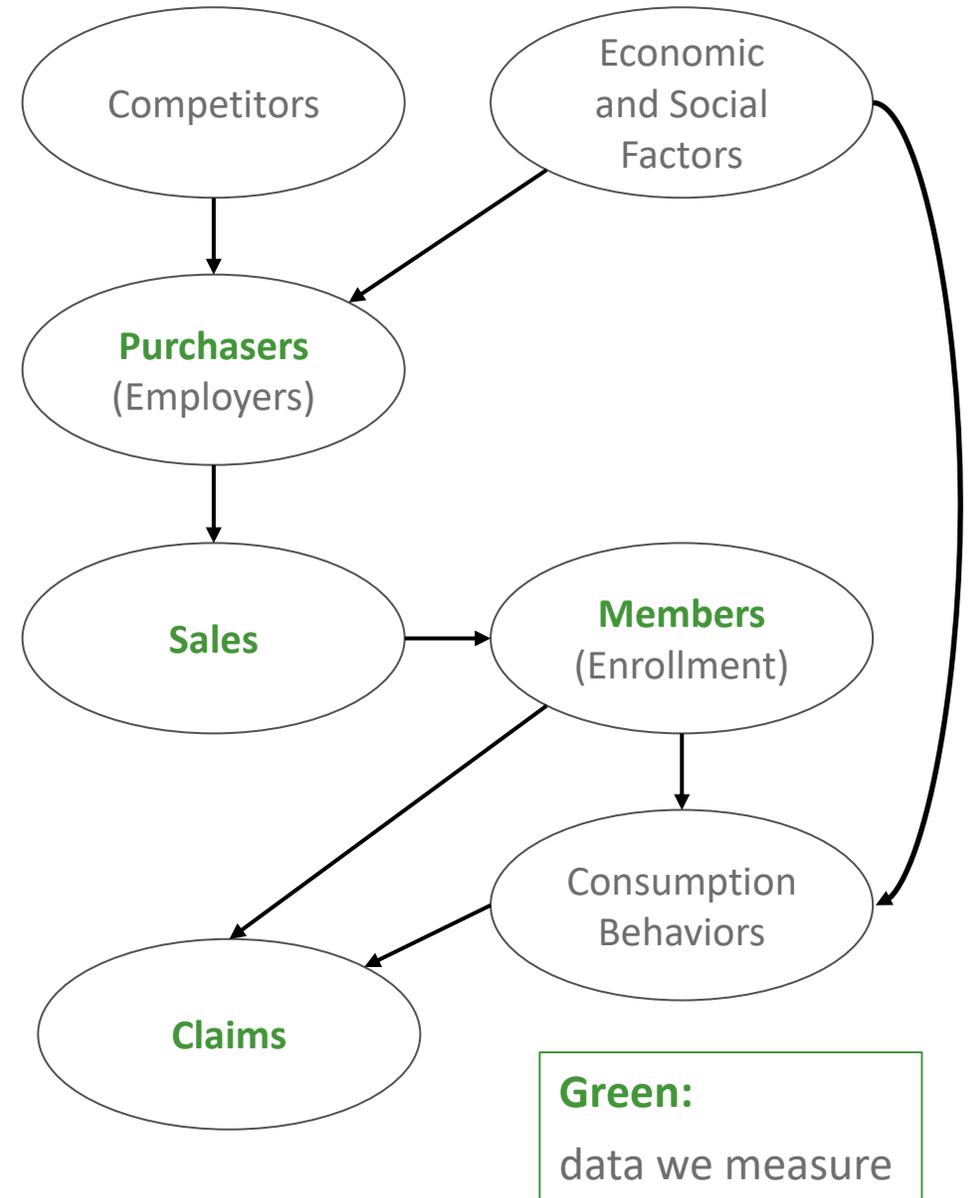
Causal models

Model = holidays + externals + seasonality + trend + noise



Implies: A good causal model will have:

- ▶ Trend ~ constant and, ideally, ~ zero
- ▶ $\text{stddev}(\text{trend}) < \sim \text{stddev}(\text{noise})$



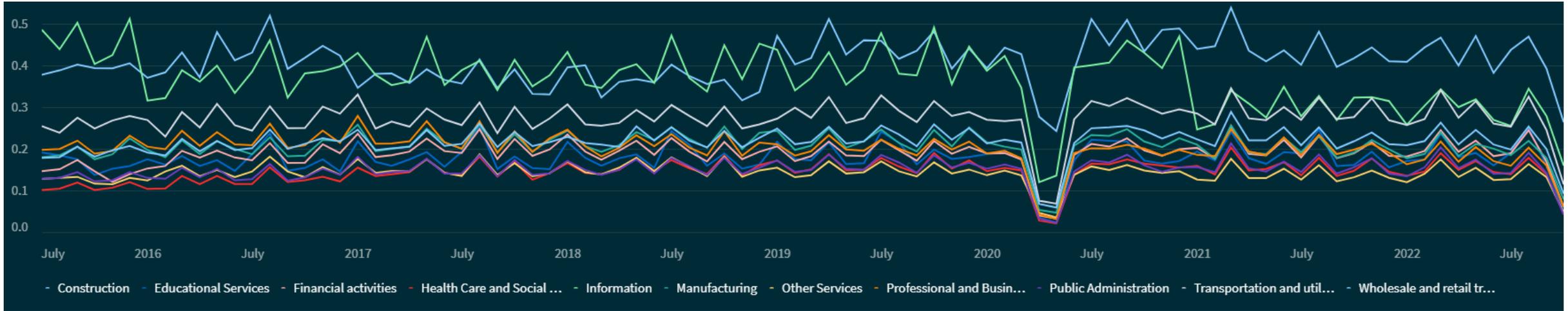
Question 1 - Leading indicators for our business

- ▶ Downloaded series from the [St Louis Federal Reserve](#)
- ▶ Currently collecting 102 series and 152 months of data.
- ▶ Coverage:
 - ▶ Selected USA Federal Series
 - ▶ Selected OECD Series for the USA
 - ▶ Selected NJ State Level Series
 - ▶ Industry Sector Series for (where available):
 - ▶ USA Real GDP
 - ▶ USA Employment Cost Index
 - ▶ NJ Real GDP
 - ▶ NJ Employment
 - ▶ NJ Job Openings
- ▶ Added NJ COVID caseloads from [The New York Times](#)
- ▶ Added US Treasury Income Tax Refunds issued

Selecting Series

1. Start with about 30-35 series per sector
2. Identify series that add information
 - ▶ Null hypothesis: series is collinear with other series in the indicators group
 - ▶ Test: [Variance Inflation Factor](#)
 - ▶ Outcome: Series with $VIF \leq 10$ are not strongly collinear
3. Then select series that may predict claims volume
 - ▶ Null hypothesis: Series is not a significant predictor
 - ▶ Test: [Granger Causality](#)
 - ▶ Outcome: Series with p-value ≤ 0.05 are probable predictors
4. Finish with 6-15 candidates for modeling

Preventive and Diagnostic: claim lines per enrollee for each sector



- ▶ P&D dental claims usually have 2 or 3 lines (dental procedures) for each visit
- ▶ Almost all our members are 100% covered for two routine visits a year with no copay
- ▶ P&D makes up about 70% of claims and about 50% of fees paid
- ▶ Y-axis is number of claim lines per employee per month.
- ▶ Aside from the COVID lockdown the series are basically stationary; trend and variation are not changing much
- ▶ The three highest sectors (Construction, Information Services, Transportation & Utilities) have low enrollment so their impact on the totals across the business is small.
- ▶ The NetFee per enrollee series (amount of money paid out on claims) tracks the claim counts closely so we just use the counts.

Common Economic Series – Preventative and Diagnostic

Number of industry sectors each of the most likely predictor economic series appears in. Only those appearing in at least half of the 14 sectors are listed. The modeling target is number of claims per enrolled member per month.

Before Covid: July 2015 to February 2020

Series id	Sectors	Series title
ACTLISCOUNJ	12	Housing Inventory: Active Listing Count in New Jersey
PIREDCOUMMNJ	8	Housing Inventory: Price Reduced Count Month-Over-Month in New Jersey
LBSSA34	8	Labor Force Participation Rate for New Jersey
IRSTAXREFUNDSBUSINESS	7	IRS Tax Refunds Business
CMRMT	7	Real Manufacturing and Trade Industries Sales
SMS34000006561000001	7	All Employees: Education and Health Services: Educational Services in New Jersey

Entire Period: July 2015 to October 2022

Series id	Sectors	Series title
COVIDNJ	14	Covid case counts for New Jersey
BRNJ34M647NCEN	13	SNAP Benefits Recipients in New Jersey
FEDFUNDS	11	Federal Funds Effective Rate
CSCICP03USM665S	11	Consumer Opinion Surveys: Confidence Indicators: Composite Indicators: OECD Indicator for the United States
IRSADVANCEDCHILDTAXCREDIT	10	IRS - Advanced Child Tax Credit
IRSTAXREFUNDSINDIVIDUAL	10	IRS Tax Refunds Individual
UMCSENT	9	University of Michigan: Consumer Sentiment
PIREDCOUMMNJ	9	Housing Inventory: Price Reduced Count Month-Over-Month in New Jersey

Predictor Series: Sector – Educational Services

Preventative & Diagnostic, Pre-COVID

Largest sector by enrolled member count in the fully insured business

series_id	VIF	p-value	title
ACTLISCOUNJ	3.60	0.0000	Housing Inventory: Active Listing Count in New Jersey
CMRMT	4.89	0.0035	Real Manufacturing and Trade Industries Sales
SMS34000006561000001	6.45	0.0200	All Employees: Education and Health Services: Educational Services in New Jersey
CIS2016100000000I	4.62	0.0205	Employment Cost Index: Total compensation for Private industry workers in Education services
LBSSA34	5.62	0.0367	Labor Force Participation Rate for New Jersey
INDPRO	6.56	0.0374	Industrial Production: Total Index

Educational Services	
total_counts_per_enrollee	10.0208
cumulative_counts_per_enrollee	218.5908
percent_counts_per_enrollee	4.1197

Table 7 - Likely predictor series for industry sector Educational Services. List of economic indicator series for Educational Services that pass Variable Influence Factor (VIF) test *and* Granger Causality tests. There were 41 series checked, 6 were accepted with VIF values less than 10.0 and Granger Causality p-values less than 0.05 significance level. The series are sorted in descending order of [approximate] statistical significance.

Predictor Series: Sector – Health Care and Social Assistance

Preventative & Diagnostic, Pre-COVID

Third largest sector by enrolled member count in the fully insured business

series_id	VIF	p-value	title
PRIREDCOUMMNJ	4.87	0.0004	Housing Inventory: Price Reduced Count Month-Over-Month in New Jersey
SMS34000006561000001	4.34	0.0005	All Employees: Education and Health Services: Educational Services in New Jersey
ACTLISCOUNJ	4.60	0.0009	Housing Inventory: Active Listing Count in New Jersey
CMRMT	6.76	0.0168	Real Manufacturing and Trade Industries Sales
LBSSA34	7.57	0.0195	Labor Force Participation Rate for New Jersey
JTS6200JOL	9.93	0.0229	Job Openings: Health Care and Social Assistance

Health Care and Social Assistance	
total_counts_per_enrollee	8.0003
cumulative_counts_per_enrollee	243.24
percent_counts_per_enrollee	3.2891

Table 13 - Likely predictor series for industry sector Health Care and Social Assistance. List of economic indicator series for Health Care and Social Assistance that pass Variable Influence Factor (VIF) test and Granger Causality tests. There were 42 series checked, 6 were accepted with VIF values less than 10.0 and Granger Causality p-values less than 0.05 significance level. The series are sorted in descending order of [approximate] statistical significance.



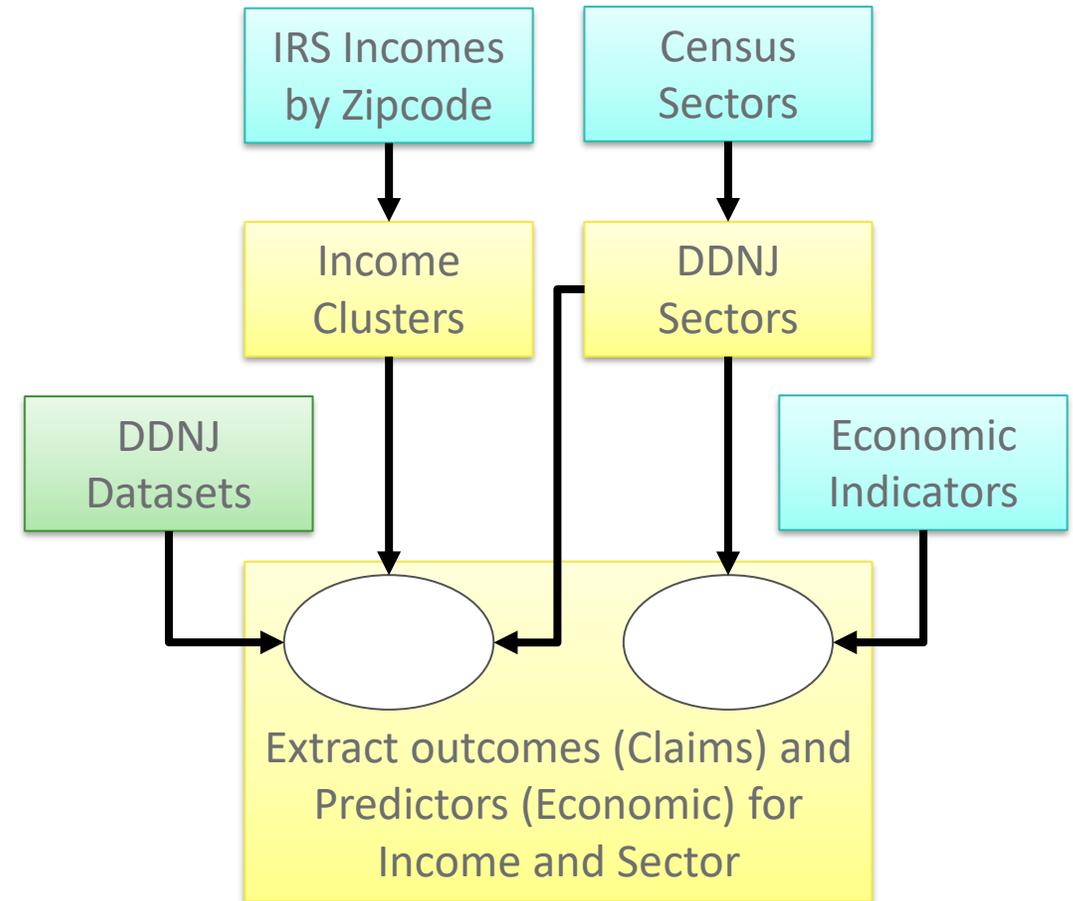
Modeling enrollee behavior

Time series modeling

We look to build a prediction model in two steps

- ▶ First: understand what factors drive changes in claims utilization. For example:
 - ▶ Trend: the business is growing, more members means more claims
 - ▶ Seasonality: we know teachers tend to visit the dentist in the summer breaks; construction workers may be the opposite
 - ▶ External economic factors: anything from GDP, employment opportunities, consumer confidence. These could be national, state, local, or industry specific. These are known as *indicators, predictors, or regressors*.
 - ▶ Income also affects utilization of procedures
- ▶ Second: train and validate model

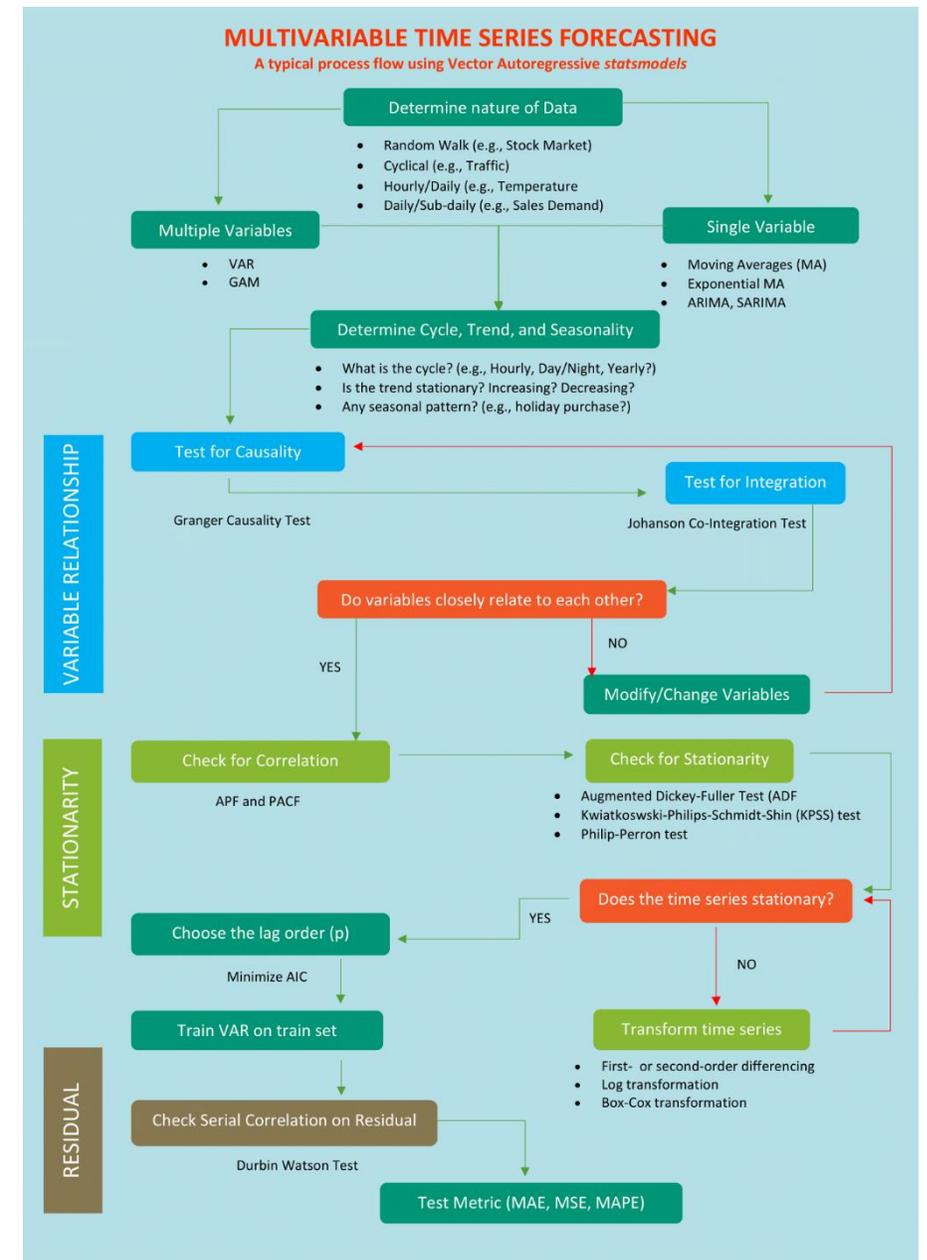
Time series construction



Putting it together

Process

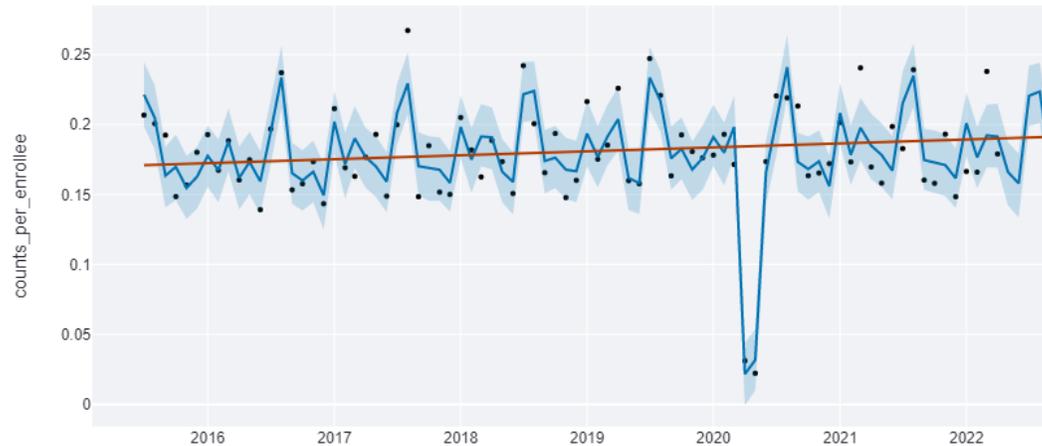
- ▶ Standardize to monthly frequency,
 - ▶ Aggregate more frequent series (weekly or daily) by summing
 - ▶ Interpolate quarterly or annual series (fitting a cubic spline)
- ▶ Extrapolate series (if necessary) to a common end date by fitting a cubic curve to the data
- ▶ For each sector and income cluster:
 - ▶ Collect the national, state, and relevant sector series
 - ▶ Check for redundant economic indicators (VIF)
 - ▶ Join to the claims (outcome) series
 - ▶ Preprocess all series to stationary form, statistical tests
 - ▶ Identify economic series that *may* be leading indicators for the claims, Granger Causality
 - ▶ Drop series that do not pass the VIF or Granger tests
 - ▶ Fit times series model to the selected collection
 - ▶ Adjust hyperparameter[s] to find a good fit. Currently by hand, automate in next phase
- ▶ **Note:** Packaged models like Meta's Prophet will perform many of the steps automatically. But exposing them like this helps identify relevant inputs and makes it easier to *explain* what is going on.



Source

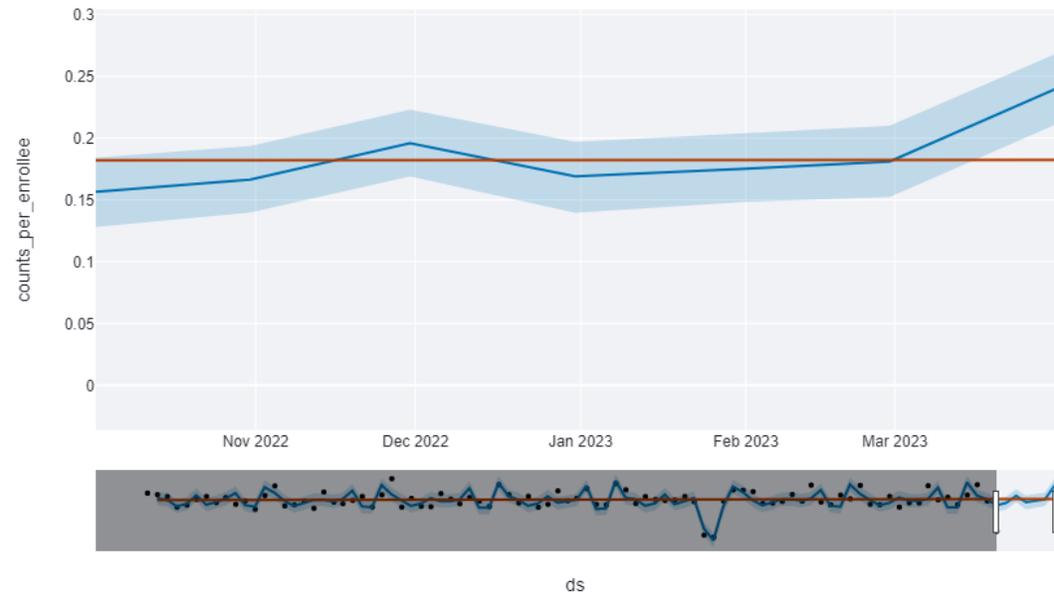
Question 2 - Forecasting

Middle Income 06109, Educational Services, P&D claims – six month forecast



- The blue line shows the **predictions** made by the model
- The blue shade around is an **80% uncertainty interval** on these predictions, obtained by a Monte Carlo simulation.
- The black points are the **actual values** of the target on training period.
- The red line is the **trend** estimated by the model
- Mean Absolute Percentage Error (MAPE) is ~6.5%

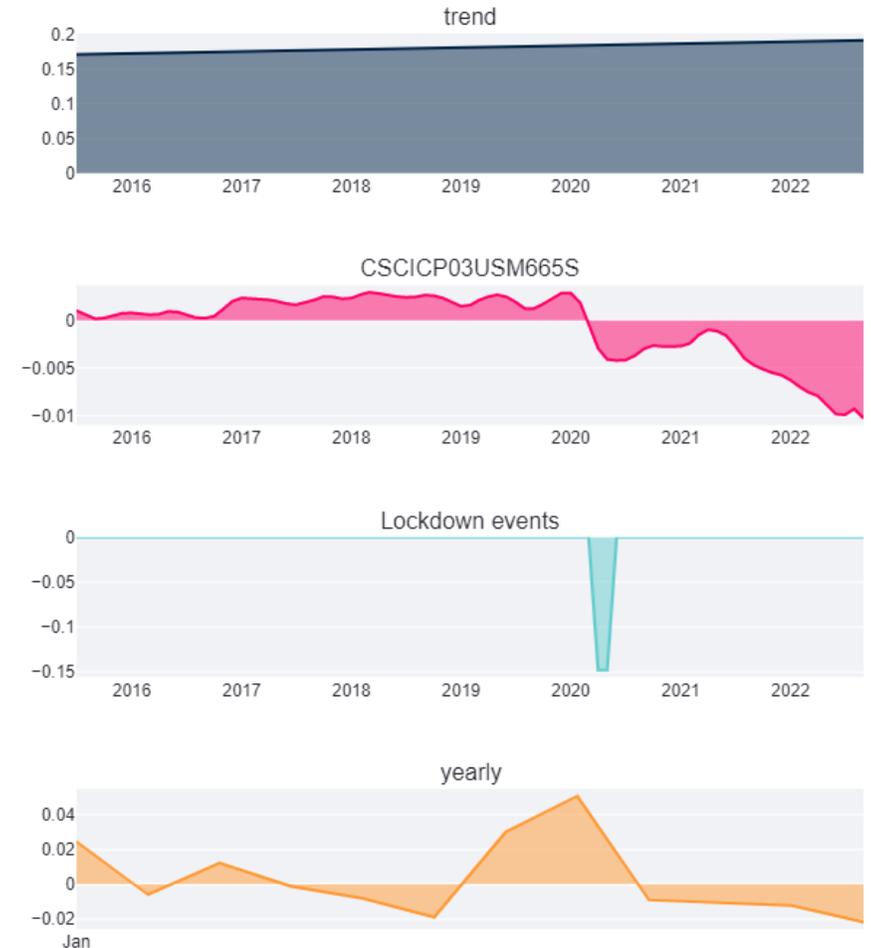
- Left: claims per enrollee for July 2015 through September 2022
- Below: Forecast for October 2022 through March 2023
- Inputs: Claims per Enrollee, Lockdown dates, OECD Confidence Indicator for the United States
- Model: Prophet, default parameters



Prophet – Time Series Forecasting

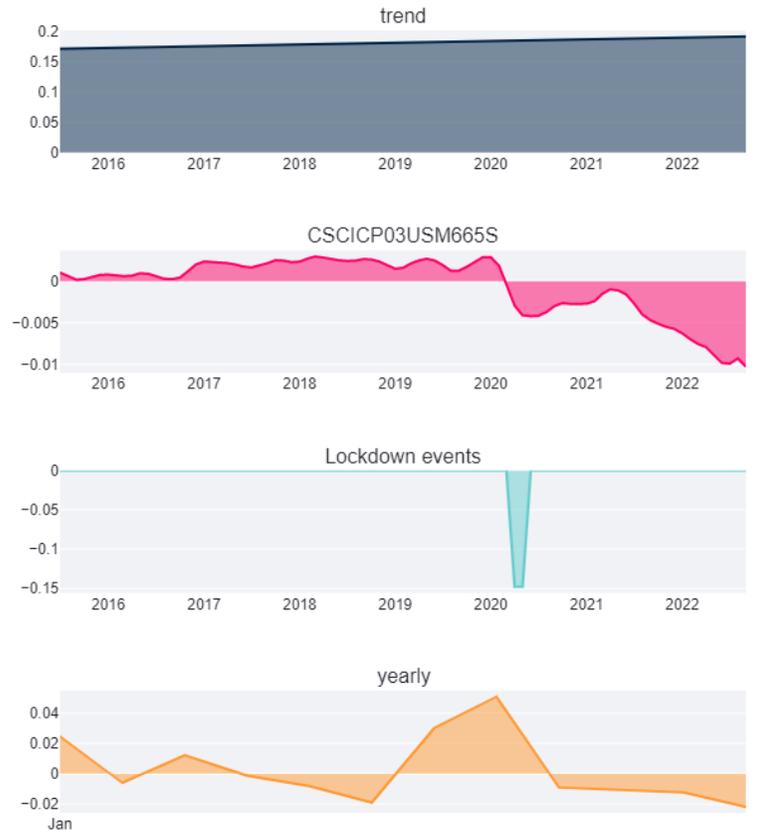
Prophet is a procedure for forecasting time series data

- ▶ Prophet is based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.
- ▶ It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well.
- ▶ Prophet is easy to use, the automatic defaults work well in many cases. It provides clear diagnostics for the model components and good guides for tuning the parameters.
- ▶ Prophet is open-source software released by Meta’s Core Data Science team. It is available in R and Python.
- ▶ DDNJ uses the Python implementation, mainly with the Streamlit Prophet GUI interface.
- ▶ We also plan to evaluate other models, see the next stage slide



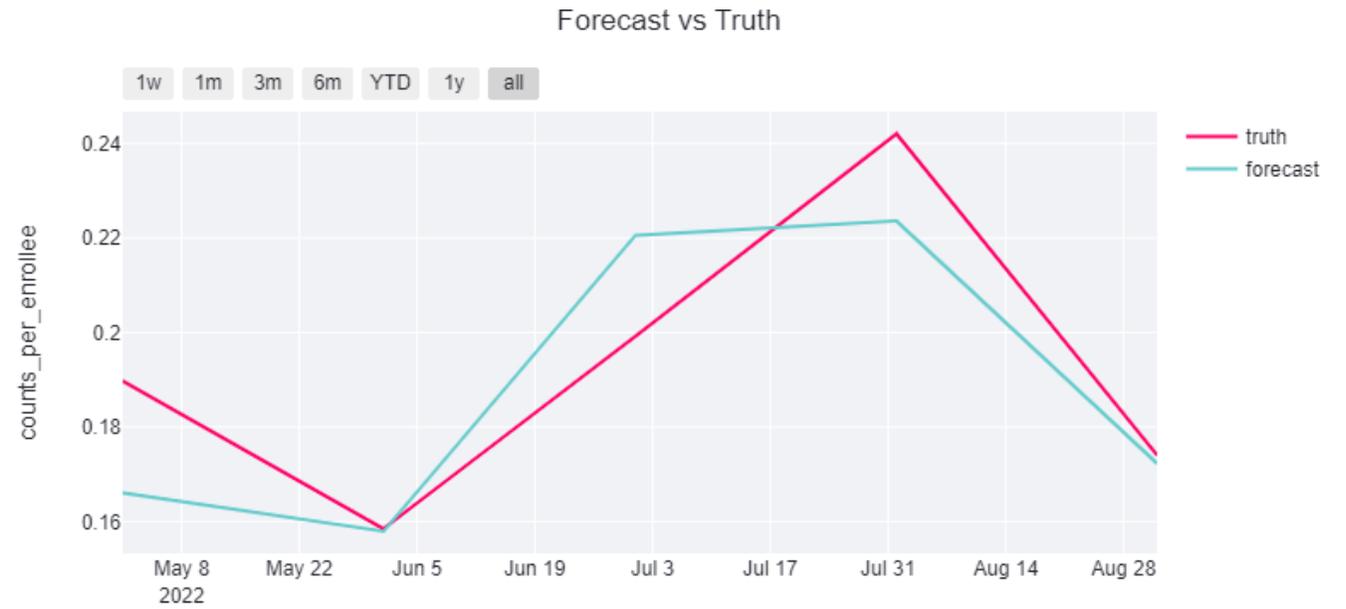
- ▶ Trend component
- ▶ External series
- ▶ Lockdown shock (using holidays)
- ▶ Seasonality (yearly here)

Explaining the Model: Educational Services – Income cluster 06109



How each component contributes to the fitted model.

- ▶ Education uses benefits in summer!



Comparing forecast on the validation run with the actual claims.



Looking across Income Groupings

High, Middle and Low Incomes, Educational Services, P&D claims

High Income, cluster 06109

Series name	Regressor	Yearly	Trend	MAPE
BRNJ34M647NCEN	-0.003			
UMCSENT	+0.001	+0.017	0.21	0.099

SNAP Benefits Recipients in New Jersey

University of Michigan: Consumer Sentiment

Middle Income, cluster 06109

Series name	Regressor	Yearly	Trend	MAPE
CSCICP03USM665S	-0.01	+0.01	0.19	0.064

Employment Cost Index: Total compensation for Private industry workers in Education and health services

Low Income, cluster 07206

Series name	Regressor	Yearly	Trend	MAPE
UMCSENT	-0.037	+0.05	0.14	0.029

University of Michigan: Consumer Sentiment

- ▶ The tables give the averaged contribution of each component of the models over the *validation* period May – September 2022
- ▶ Prophet is an *additive* model so the sum of these is the *forecast* of the claims per enrollee
- ▶ Trend – approximates the average claims / enrollee
- ▶ Yearly – How much the seasonality adds in
- ▶ Regressor – The contribution of the external series
- ▶ MAPE – Mean Absolute Percentage Error between the *forecast* and the actuals

Note

- ▶ The baseline activity of the enrollees is sensitive to income, especially low incomes
- ▶ The contribution of the external series is much smaller for high incomes

Next stage work

Data

- ▶ Aggregation processes for sparse, low claim count series (in progress)
- ▶ Econometric series extrapolation to refine forecasting

Models

- ▶ Automate running models for all series
- ▶ Evaluate Vector Autoregression (VAR)
- ▶ Evaluate advanced models:
 - ▶ Temporal Fusion Transformers (Google)
 - ▶ Causal Impact (Google)
 - ▶ ...
- ▶ Planning to use the [Darts](#) package for Python

Experiments and evaluations

- ▶ Hyperparameter tuning:
 - ▶ Various combinations of external series
 - ▶ Model parameters for each combination
 - ▶ Ensembles, aggregate forecasts
- ▶ Corrections for varying sample sizes when comparing subgroups

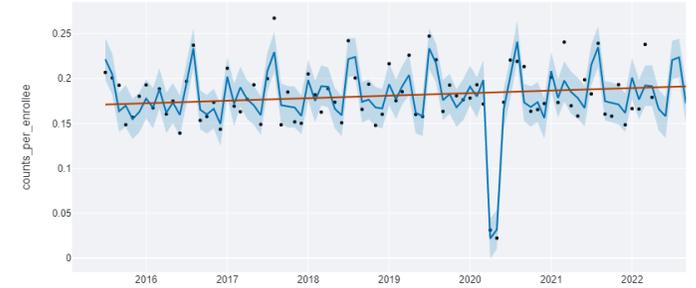
Deployment and performance

- ▶ Migrate claims queries to new Google Cloud tables
- ▶ Create configuration files for shared definitions and defaults
- ▶ Refactor code base to eliminate duplication and prepare for cloud service deployment

Recap

The Asks

1. Can we identify leading indicators for our business; especially for a recession/downturn?
2. Can we improve our end of year forecasting for the budget cycle; more accurate forecast and/or lower spread?
3. Can we improve estimates of the expected margin when underwriting a group?
4. Can we flag claims that are out of the ordinary (anomalies) for additional review?
5. Can we identify providers who are making unusual numbers or types of claims for restorations?



Where we are

- ▶ Developing models for
 - ▶ Preventative & Diagnostic claims for (70% of claims, 50% of fees)
 - ▶ Restorations (fillings) next biggest segment
- ▶ Found Economic Series that are likely indicators across the business
- ▶ For each of 14 industry sectors found between 3 and 14 series potentially usable as indicators for the claims volume
- ▶ Fitting models to claims time series for sector + member income groupings
- ▶ Working with monthly data from 2015 onwards

Thank You!

Questions?

“Neither the Voice of Authority, not the Weight of Reason or Argument, are as Significant as Experiment, for thence comes Quiet to the Mind.”

Roger Bacon, De Erroribus Medicorum, Oxford, ca 1254 CE