

2023 Blue Shield of California Case Competition

Team 11

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Agenda

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Introduction

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Manual Trend

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Introduction

Introduction - Trend Prediction Logic

- **Weighted Average**
 - Weight of Dollars (Allowed) and Utilization
 - For markets / LOBs
 - Event-Modified
- **Linear Model**
- **Limited Fluctuation Method**

1 Introduction - Major Assumption

- Monthly Weights (Utilization, Allowed) are similar in 2021 and 2022.
- Historical Trends are fully credible.
- Half-Year Trends between 2 near years are similar to their Whole-Year Trends

1 Introduction - Major Adjustment

Manual Trend:

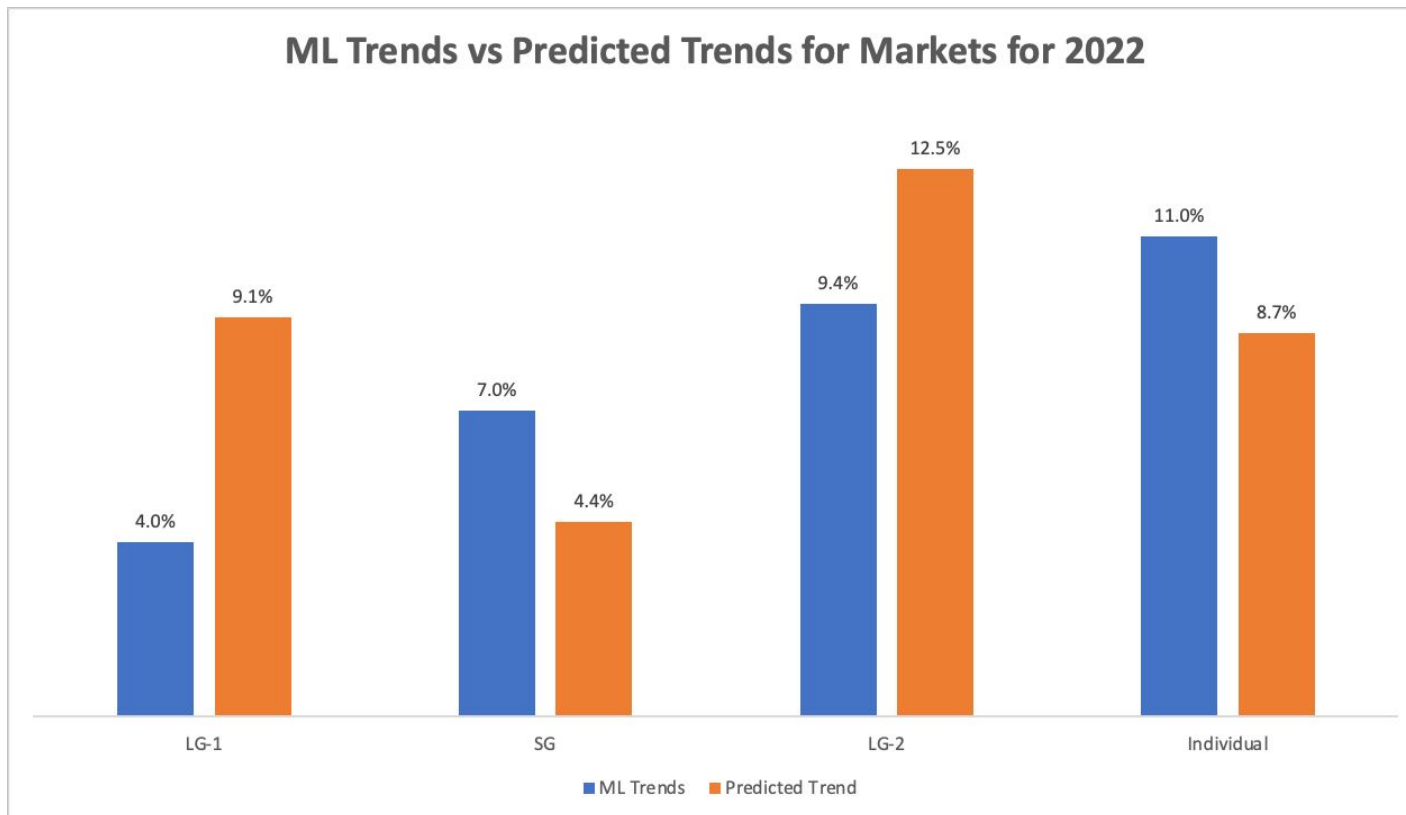
- Taking out 2019 Prof LOB because of extremely high irregular trends.
- Affected by COVID-19, taking out entire 2020 year data.

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Introduction - Major Adjustment, Examples

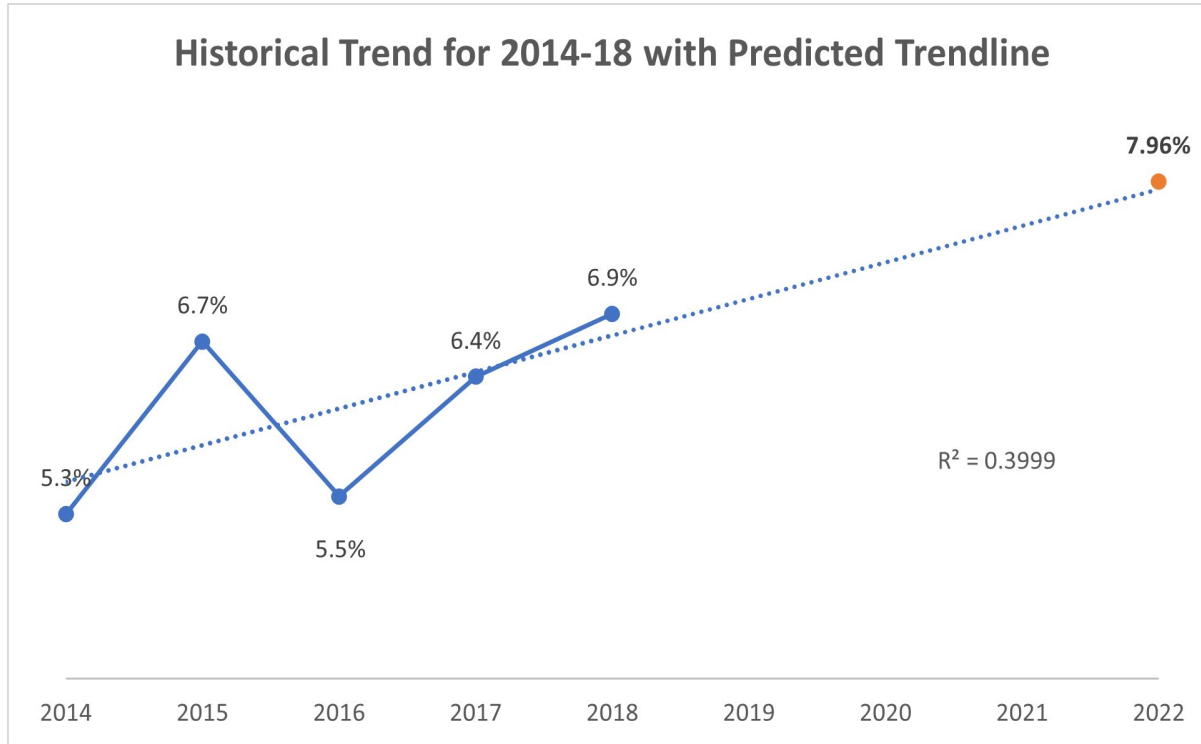
Year	Market	Type of Service	Unit Cost	Utilization
2020	LG-1	Prof	-41.0%	113.3%
2020	LG-2	Prof	-42.0%	90.6%
2020	Individual	Prof	-14.6%	38.1%
2020	Individual	Brand	16.0%	-2.1%
2019	LG-1	Prof	98.1%	3.9%
2019	LG-2	Prof	195.5%	240.5%
2019	SG	Prof	20.1%	110.7%
2019	Individual	Prof	33.6%	-16.7%

Introduction - Major Adjustment, Results



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Introduction - Why Linear Model



R-Squared = 40%

**Raw Predicted Trend:
7.96%**

Introduction - R ANOVA Table and Residuals Assumptions proved

```
7 model <- list("x" = c(2014, 2015, 2016, 2017, 2018), "y" = c(5.3, 6.7, 5.5, 6.4, 6.9))
8 model
9 linear_reg <- lm(y~x, data = model)
10 summary(linear_reg)
11 anova(linear_reg)
12
13 ### Check Residuals Assumptions
14 # Check independence
15 plot(linear_reg$residuals)
16 abline(h=0, col = "red")
17 # Check mean of residual approaches 0
18 sum(linear_reg$residuals)/5
19 # Check residuals are normally distributed
20 hist(linear_reg$residuals, breaks = c(-1, -0.3, 0.4, 1.1))
21 # Check variance of residual approaches regression variance
22 y_bar <- mean(model$y)
23 sigma_squared <- sum((model$y - y_bar)^2) / 5
24 # Residual Variance from anova: 0.41033, compare variances.
25 abs((0.41033 - sigma_squared) / sigma_squared) < 0.01 # difference is very small
```

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Introduction - Event Trend

3 affecting events

- **2021 deferred claims event:**
underlying units = data / (1 - deferred rate)
- **2022 events:**
Using monthly weights and half-year weights to annualize given event trends.

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Introduction - 2022 Event Trend

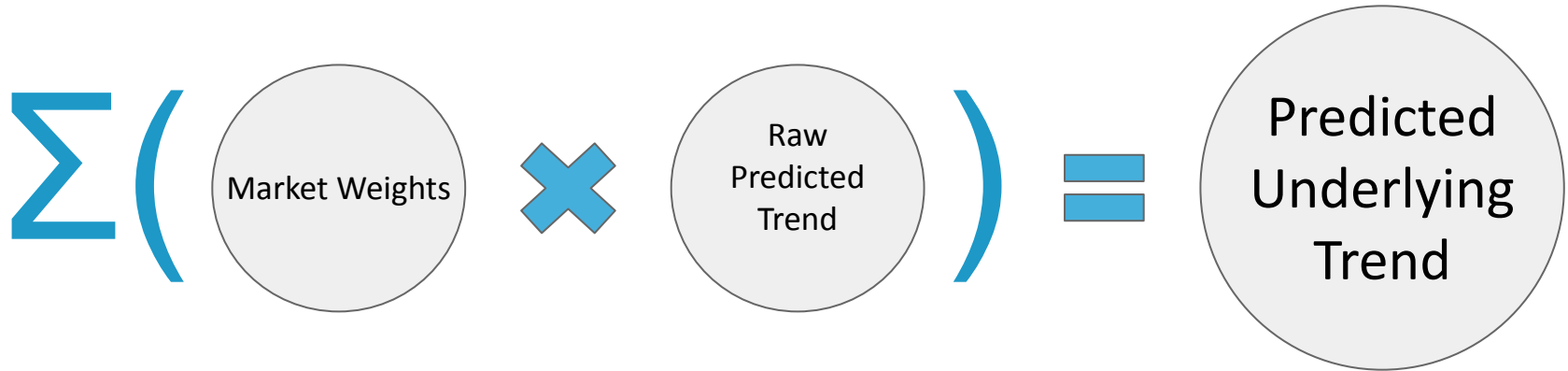
LOBs	Trend Type	Annualized Event Trend
Generic	Utilization	0.00%
	Allowed	-3.67%
	Unit Cost	-3.67%
Brand	Utilization	0.78%
	Allowed	-0.30%
	Unit Cost	-1.07%

2

Manual Trend

2

Manual Trend



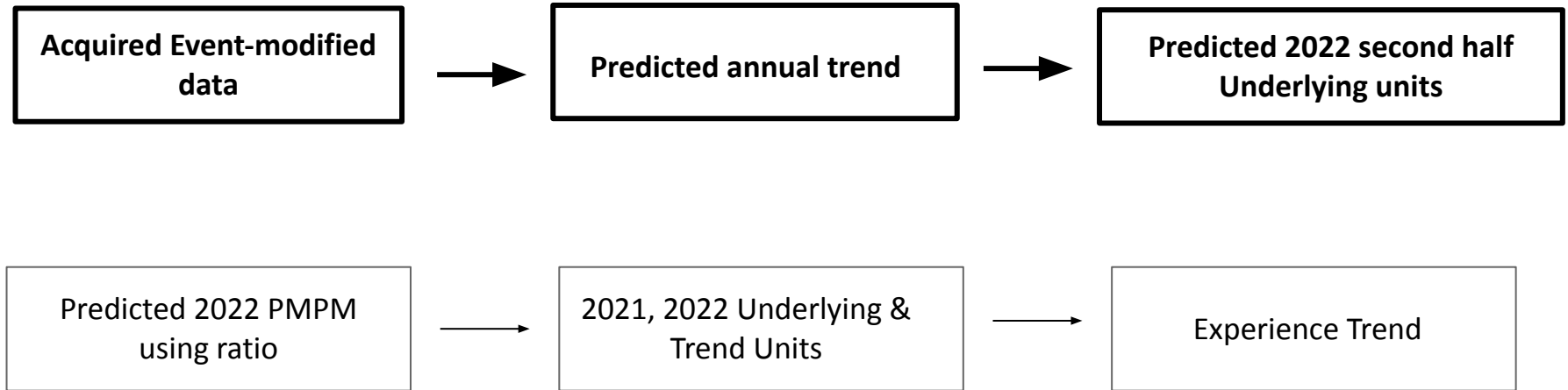
Predicted 2022 Underlying Trend		
Market	Unit Cost	Utilization
Ancillary	0.08	-0.08
Brand	0.10	-0.01
Generic	0.00031	0.0056
IP	0.07	0.02
OP	0.04	0.02
Professional	0.03	0.09

3

Experience Trend

3

Experience Trend



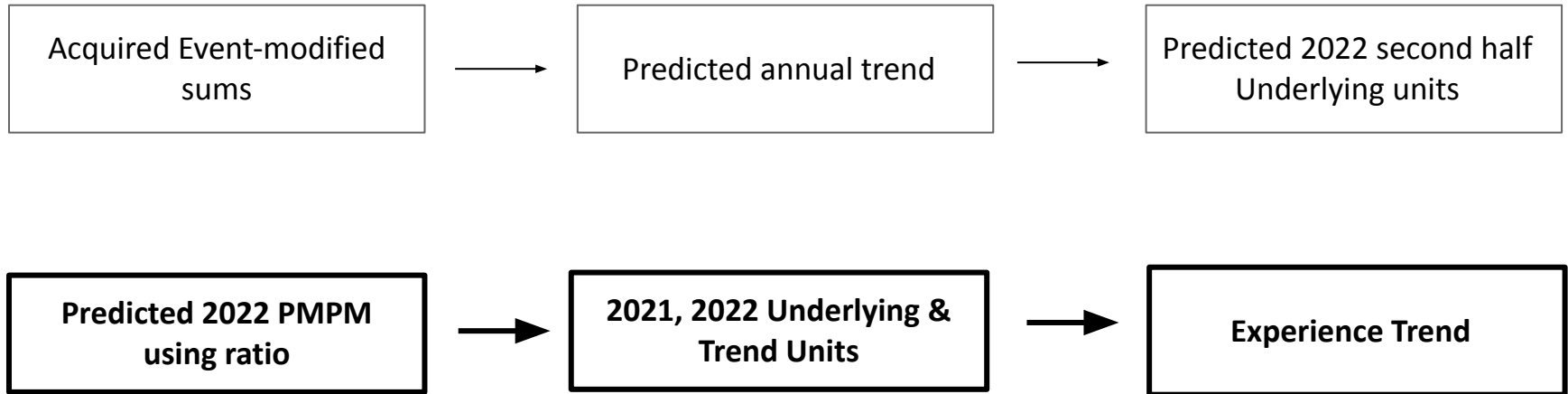
3

Experience Trend

Predicted 2022 Second Half Underlying Units		
Benefit Type	Sum of Utilization	Sum of Allowed
Ancillary	4,456,449	324,381,572
Brand	1,062,376	795,455,098
Generic	6,774,547	158,384,870
Inpatient	166,685	1,103,747,852
Outpatient	3,609,366	1,249,756,295
Professional	11,984,069	1,147,198,884
Total	28,059,099	4,773,219,413

3

Experience Trend



3

Experience Trend

2022 first half member months



2021 whole year member months

 2021 first half member months

2022 Estimated Member Months	
Ancillary	15,609,074
Brand	15,609,074
Generic	15,609,074
IP	15,609,074
OP	15,609,074
Professional	15,609,074
Total	93,654,444

3

Experience Trend

Utilization Trend			
Benefit Type	Underlying Trend	Event Trend	Adjusted Core Trend
Ancillary	6.5%	0.0%	6.5%
Brand	-2.4%	0.4%	-2.1%
Generic	3.5%	0.0%	3.5%
Inpatient	10.5%	0.0%	10.5%
Outpatient	13.4%	0.0%	13.4%
Professional	7.8%	0.0%	7.8%
Total	6.8%	0.0%	6.8%

Util/K Calculation:

(Sum of Utilization) * 12,000

Sum of Member Months

3

Experience Trend

Unit Cost Trend			
Benefit Type	Underlying Trend	Event Trend	Adjusted Core Trend
Ancillary	0.3%	0.0%	0.3%
Brand	15.7%	-0.7%	14.9%
Generic	10.6%	-3.7%	6.5%
Inpatient	-9.6%	0.0%	-9.6%
Outpatient	-4.9%	0.0%	-4.9%
Professional	0.9%	0.0%	0.9%
Total	0.1%	-0.2%	-0.1%

Unit Cost Calculation:

Sum of Allowed Dollars

Sum of Utilization

3

Experience Trend

PMPM Trend			
Benefit Type	Underlying Trend	Event Trend	Adjusted Core Trend
Ancillary	6.8%	0.0%	6.8%
Brand	12.9%	-0.3%	12.5%
Generic	14.4%	-3.7%	10.2%
Inpatient	-0.1%	0.0%	-0.1%
Outpatient	7.9%	0.0%	7.9%
Professional	8.7%	0.0%	8.7%
Total	6.9%	-0.2%	6.7%

PMPM Calculation:

$$(1 + \text{Utilization Trend}) * (1 + \text{Unit Cost Trend}) - 1$$

4

Credibility

Limited Fluctuation Method

Credibility-Weighted Rate = (Z) * (Observed Rate) + (1 - Z) * (Prior Rate)

Observed Rate = Experience Trend

Prior Rate = Manual Trend

4

Square Root Formula

$$Z = \sqrt{\frac{N_{AC}}{N_{FC}}}$$

N_{AC} = sum of member months for 2022

N_{FC} = sum of member months for 2014-2019

$$Z = \sqrt{\frac{93,654,445.86}{595,079,473.6}} = \mathbf{0.3967}$$

Weighted-Credibility Trend

$$\text{Weighted-Credibility Trend} = (0.39) * (\text{Experience Trend}) + (1 - 0.39) * (\text{Manual Trend})$$

4

Weighted-Credibility Trend

Utilization

Benefit Type	WCT
Ancillary	-2.0%
Brand	-1.0%
Generic	1.7%
Inpatient	5.3%
Outpatient	6.4%
Professional	8.6%
Total	4.7%

Unit Cost

Benefit Type	WCT
Ancillary	5.2%
Brand	11.0%
Generic	0.4%
Inpatient	0.4%
Outpatient	0.6%
Professional	1.9%
Total	3.1%

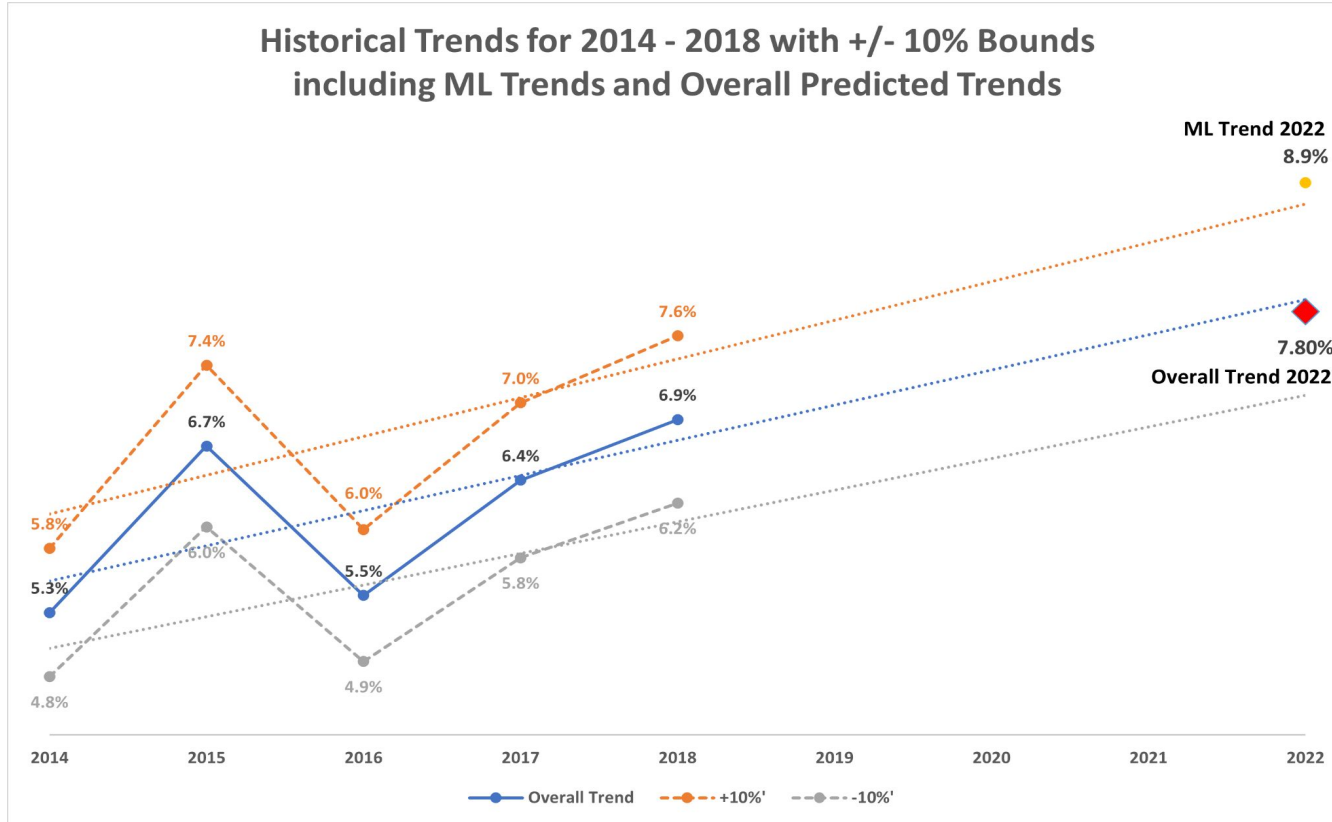
PMPM

Benefit Type	WCT
Ancillary	2.8%
Brand	9.8%
Generic	2.2%
Inpatient	5.4%
Outpatient	6.9%
Professional	10.6%
Total	7.8%

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XGBoost vs Our Trend

XGBoost ML Trend vs Weighted Credibility Trend



ML Trend 2022

8.86 %

Linear Trendline

7.96 %

**Weighted
Credibility Trend**

7.80 %

Advantages & Disadvantages of XGBoost

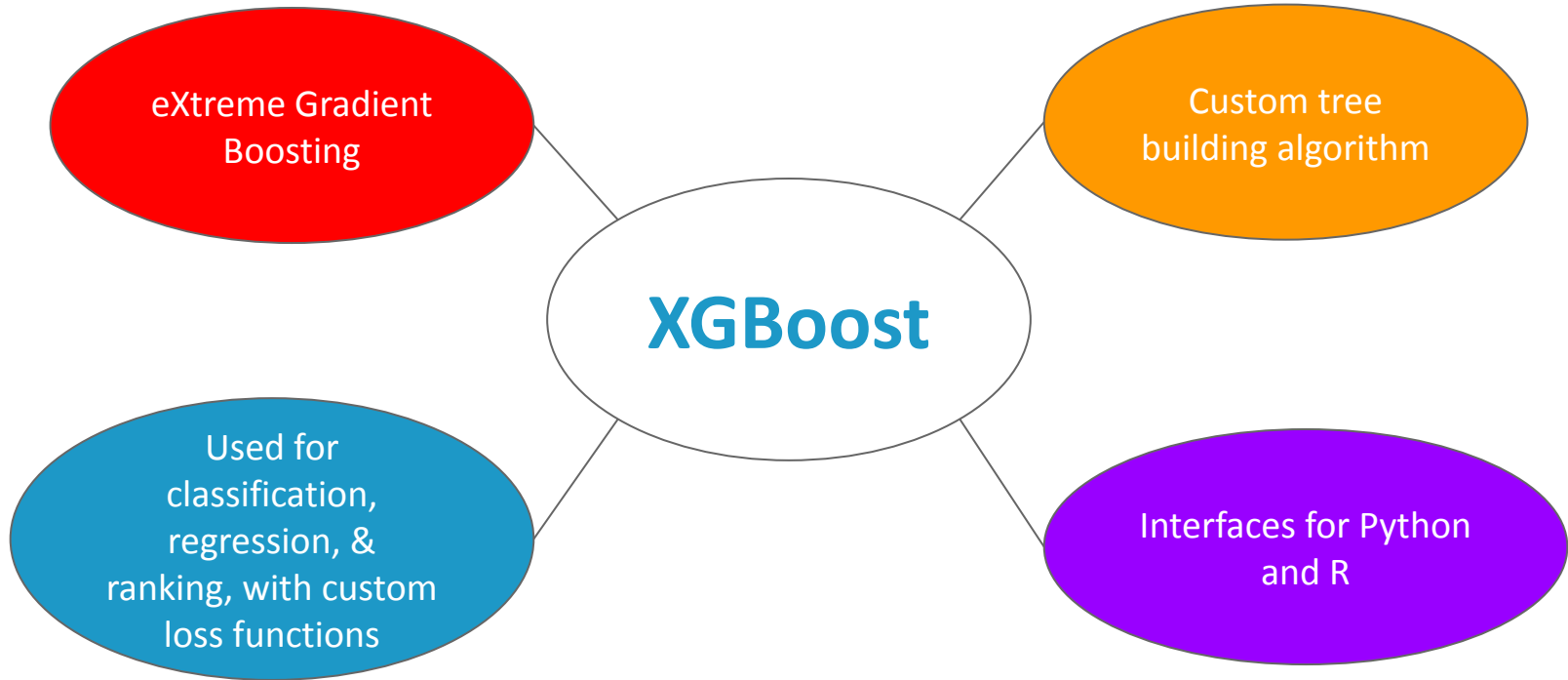
Pros

- Works well with large data sets containing more than thousands of rows
- Efficient handling of missing data
- Regularization to avoid overfitting the data

Cons

- Doesn't perform well on unstructured data
- Sensitive to outliers

Future of XGBoost in Actuarial Work



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Conclusion

- XGBoost has limitation in prediction because of its high sensitivity, but it performs well when taking care of missing data
- **Advice:**
 - XGBoost should become an assistance for actuaries, however, data selection, analysis, and scrutinization by actuaries are necessary for a better prediction.

Thank You!

Team 11