

**BA 305**

**Team 7**

# **PREDICTING INSURANCE PRICES**

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# Today's Agenda

1

**INTRODUCTION**

2

**DATASET**

3

**MODEL**

4

**MODEL RESULTS**

5

**FINDINGS**

# **1. INTRODUCTION:**

**WHY WE NEED AN  
INSURANCE PRICING MODEL**

# A Prevailing Issue in American Healthcare

U.S. MEDICAL INSURANCE HAS  
BECOME A SIZABLE AND  
FREQUENT EXPENSE

COMPLICATED BILLING SYSTEMS  
CONFUSE PATIENTS ON THEIR  
INSURANCE CHARGES

PATIENTS DO NOT KNOW  
WHETHER THEY ARE BEING  
OVERCHARGED OR NOT

Americans owe over  
**\$220,000,000,000**  
in medical debt

# OUR GOAL

To accurately predict a patient's insurance costs given their personal profile in order to provide greater pricing clarity



## **2. OUR DATASET:**

**WHAT IT IS AND HOW WE  
USED IT**

# Final Dataset After Cleaning: 2,772 -> 2,761 Datapoints

Variable	Description	Values
<b>Age</b>	Age of the patient/beneficiary	18 - 64
<b>Smoker</b>	0 = non-smoker; 1 = smoker	0 or 1
<b>Gender</b>	1 = male; 2 = female	1 or 2
<b>BMI</b>	Body Mass Index	15 - 53
<b>No. of Children</b>	Number of possible dependents covered	0 - 5
<b>Region</b>	Geographic Region	Northwest (1), Northeast (2), Southwest (3), Southeast (4)
<b>Insurance Price</b>	Total Annual Medical Charges billed by Insurer	\$1000 - \$60,000+

# Data Preprocessing

1

Removed rows  
with  
missing/unknown  
values (?)

2

Converted  
smoker and  
gender variables  
into numeric  
binary values

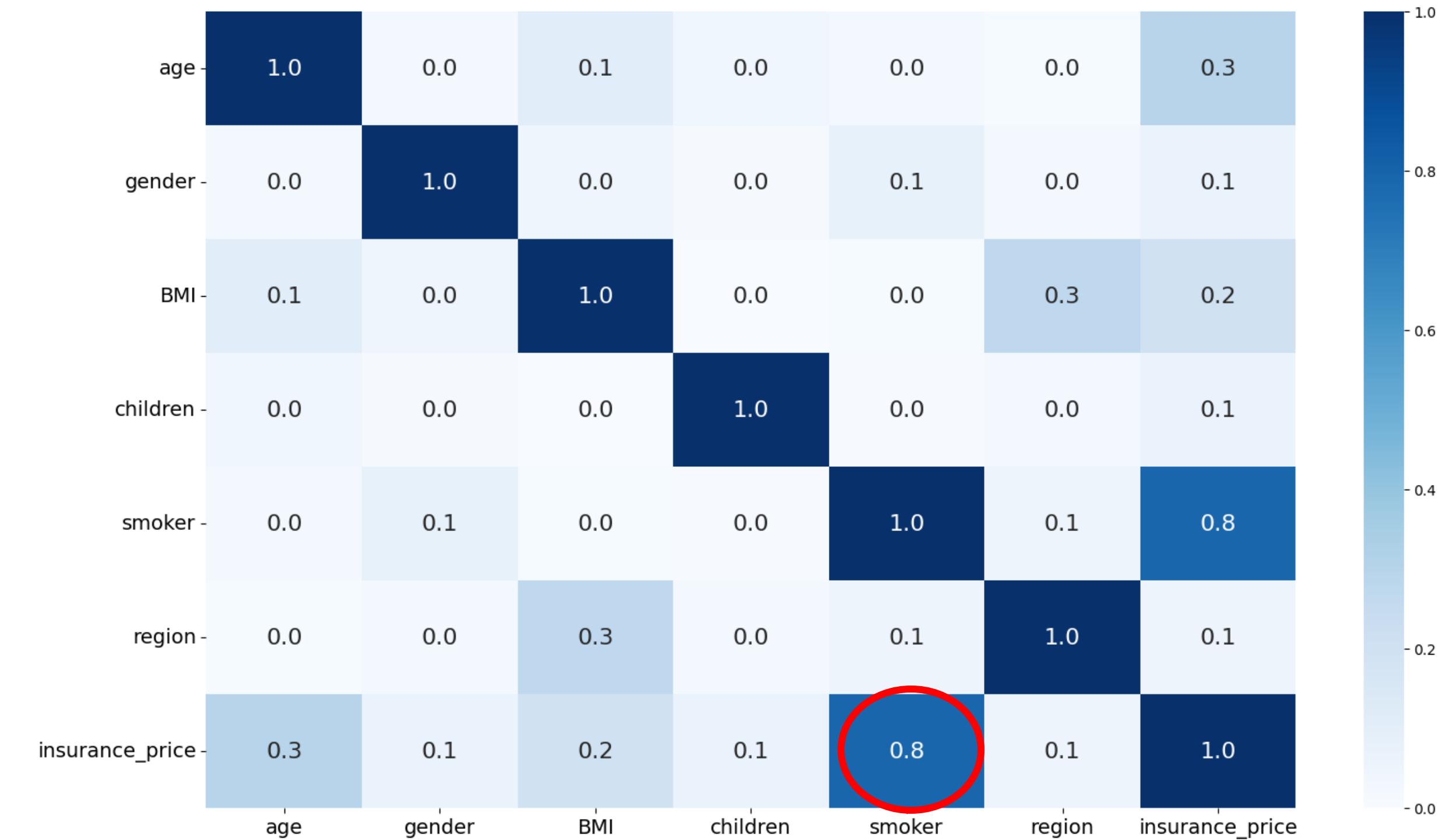
3

Applied One-  
Hot encoding  
to convert  
regions into  
numeric binary  
value

4

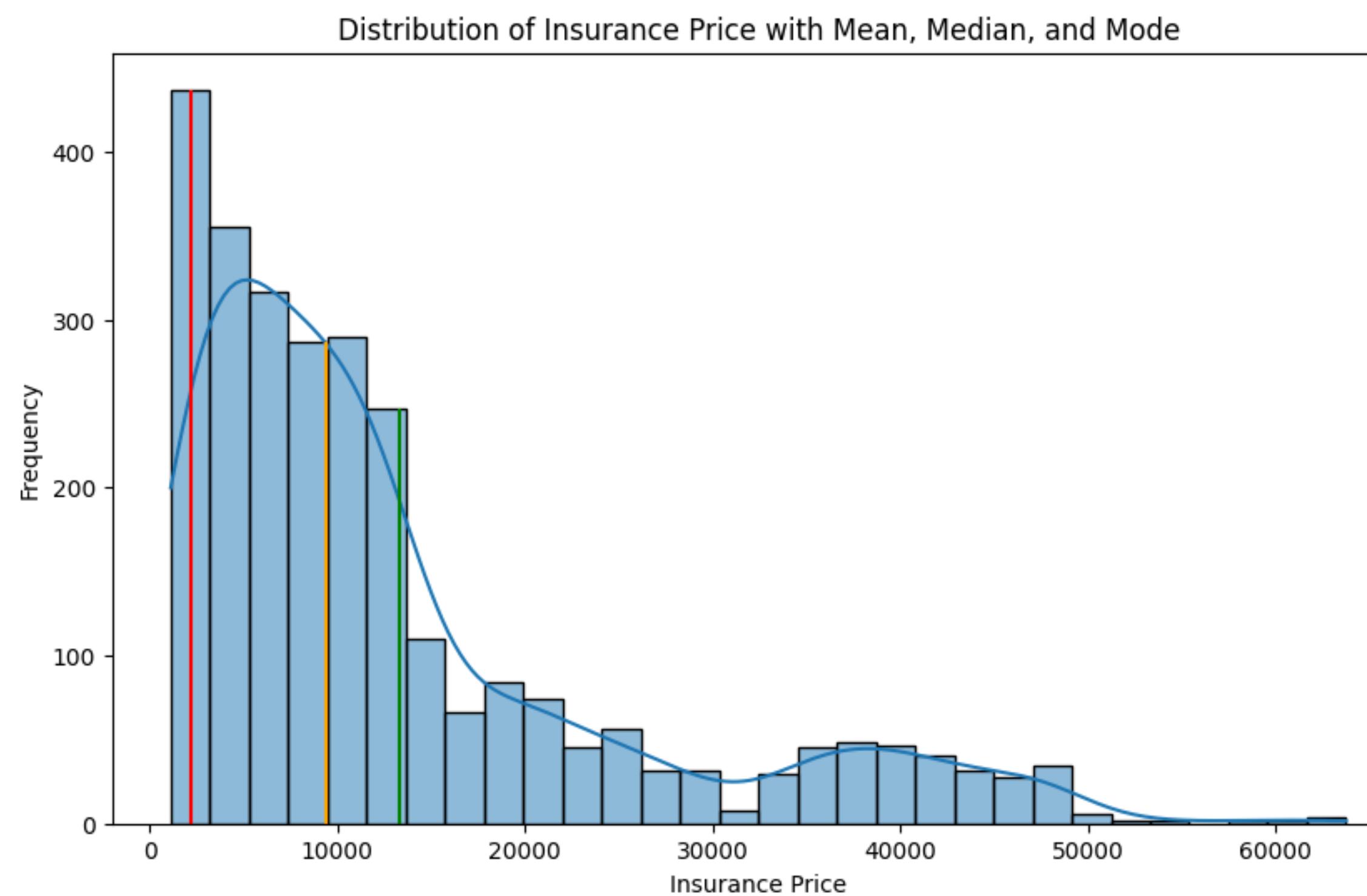
Verified data  
types

# Initial Patterns in Our Data



Strong correlation between Smoking and Insurance Charges, followed by Age and BMI.

# Our Dataset's Averages

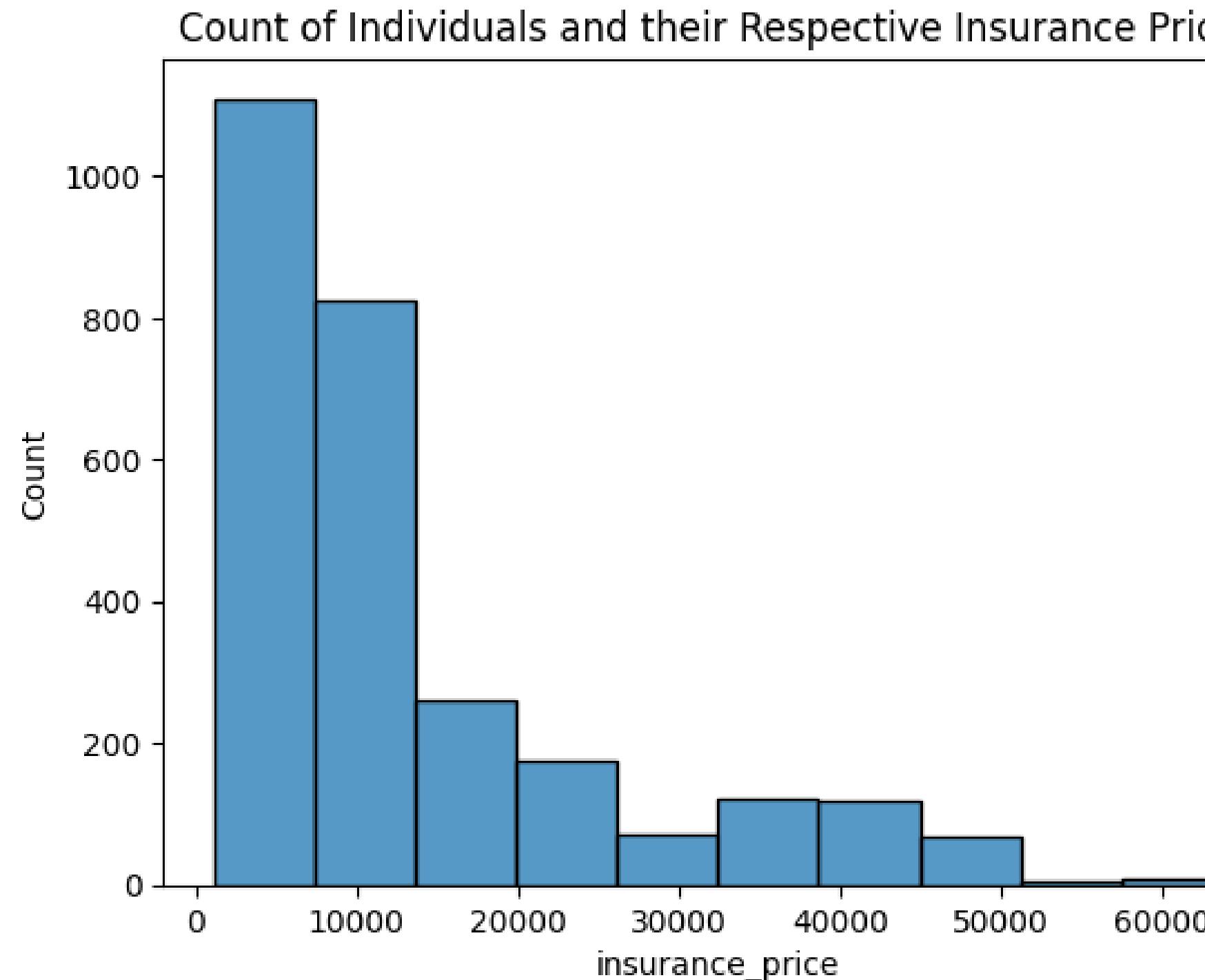


## Key:

- Mean: 13274.76
- Median: 9377.90
- Approx. Mode: 2166.02

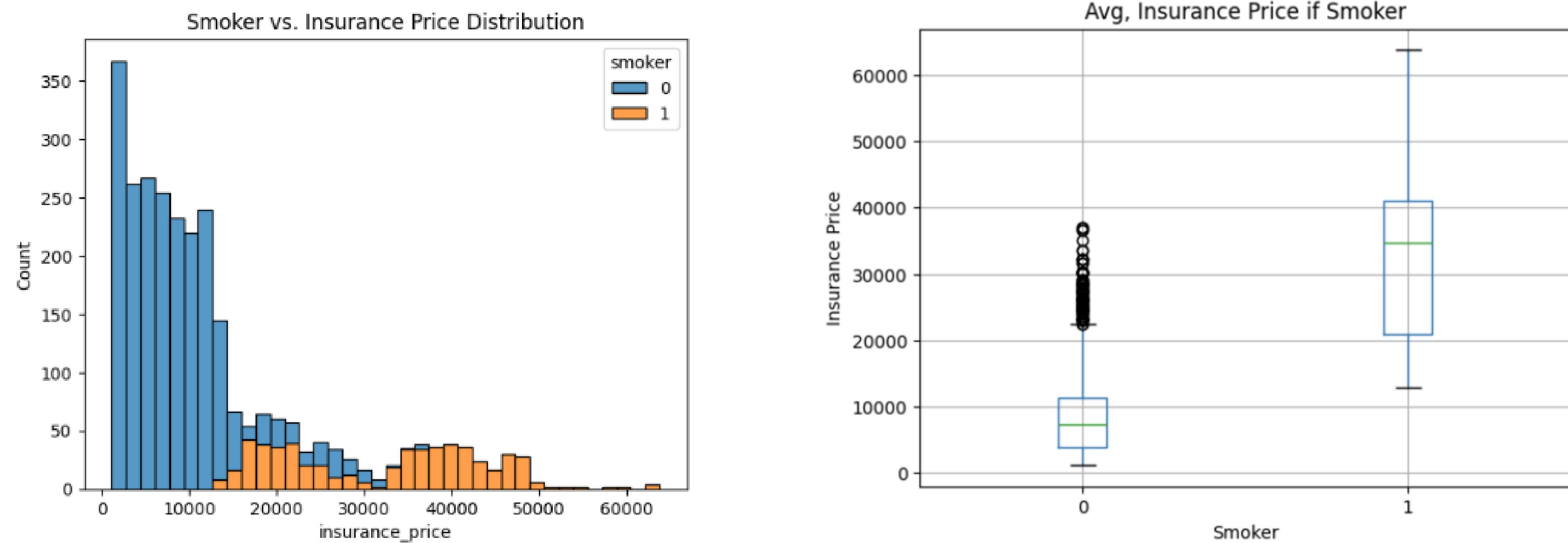
- Mean is pulled right/upward by extreme cases
- Median reflect typical costs
- Mode shows most common prices are low
- Insurance Prices are not evenly distributed

# Addressing Extreme Insurance Price Cases



- 14 users experience costs over \$50,000
- ICU stays can exceed \$4,300/day
- Removing cases would distort the true distribution

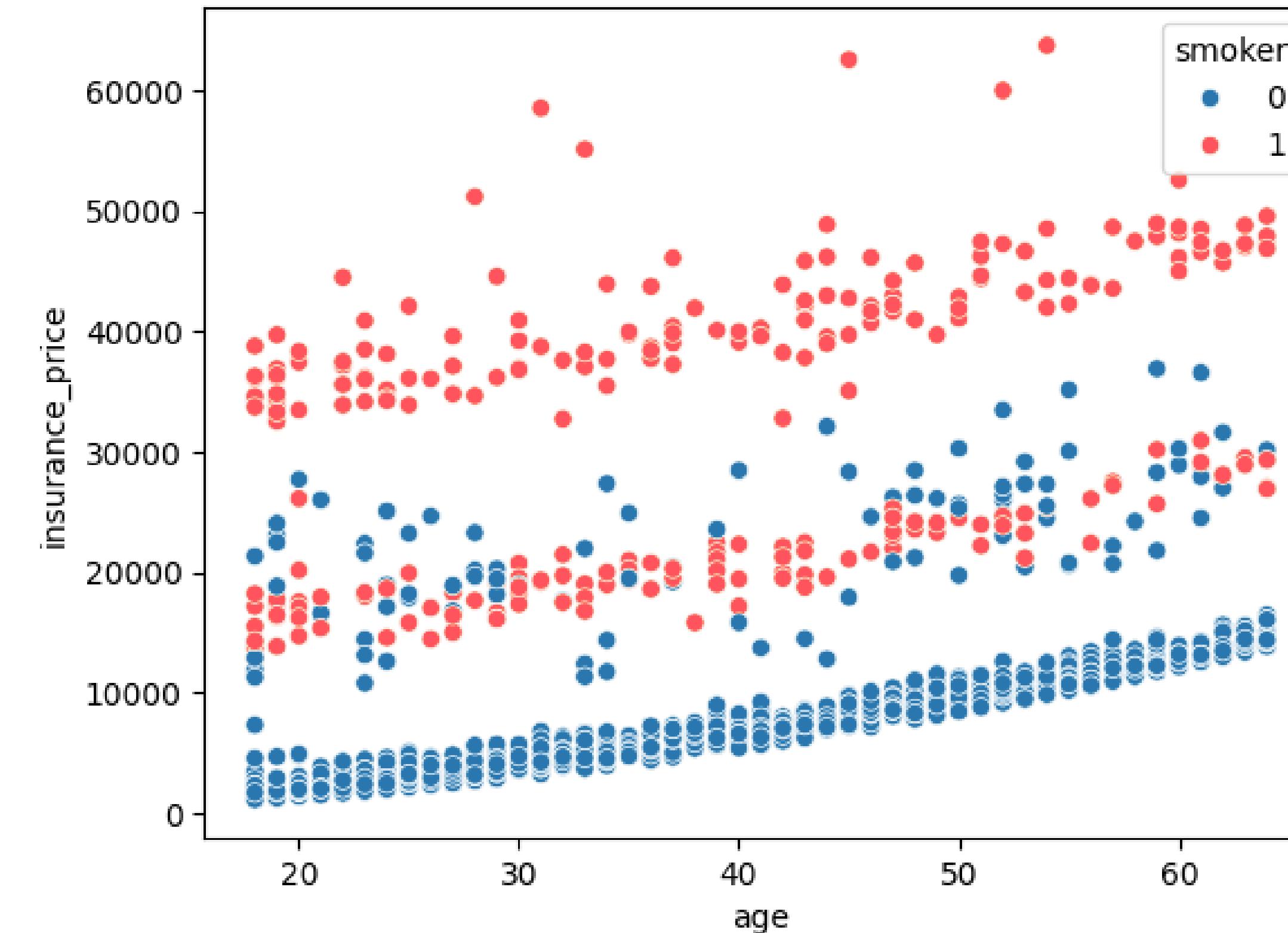
# Initial Patterns in Our Data



Smokers incur higher and more variable costs compared to non-smokers, with extreme high cases pushing annual costs.

# Abnormal Trends In Price

Age vs. Insurance Price Given Smoking Status



# **3.MODEL:**

**EXPLORATION AND  
POTENTIAL MODELS**

# Our Approach

## Step 1:

Establish a baseline performance benchmark for all subsequent models

## Step 2:

Introduce more complex, flexible models to capture relationships

## Step 3:

Evaluate the models using same training and test split, tune hyperparameters of models, when feasible, and apply 5-fold cross validation

## Step 4:

Comparison using MAE, RMSE and R-squared

## Step 5:

Building and interpreting our two stage prediction algorithm

# Comparison Criteria

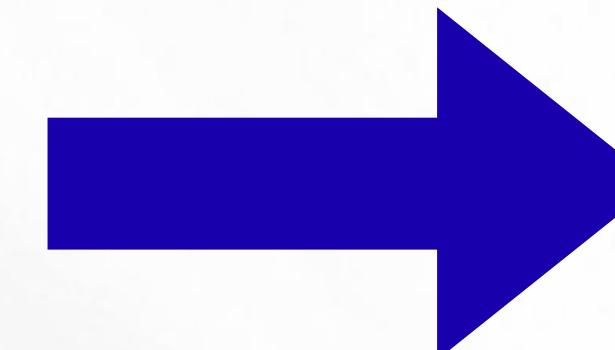
MAE	RMSE	R^2
<p>Measures absolute average difference between predictions and values.</p> <p>Simple measure of average error.</p>	<p>Measures square root of average squared error.</p> <p>Penalizes large errors.</p>	<p>Analyzes variability of model around its mean.</p> <p>AKA. how well does the model predict actual values?</p>

**BEST MODEL = CONSIDERS ALL THREE**

# Baseline Model

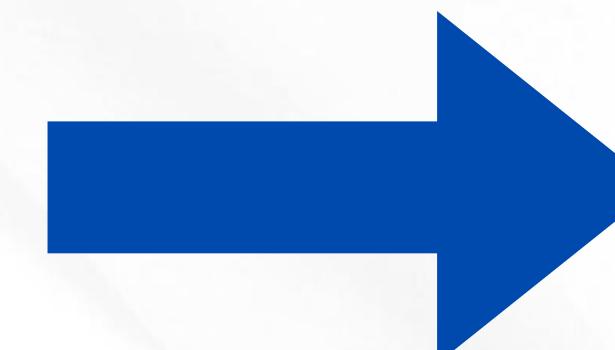
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**Naive Rule**



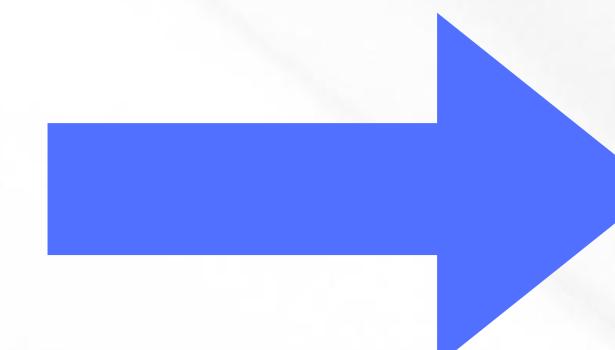
Calculate by mean

**MAE**



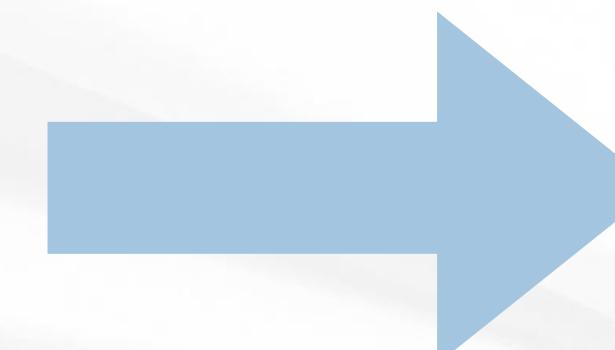
9132.437

**RMSE**



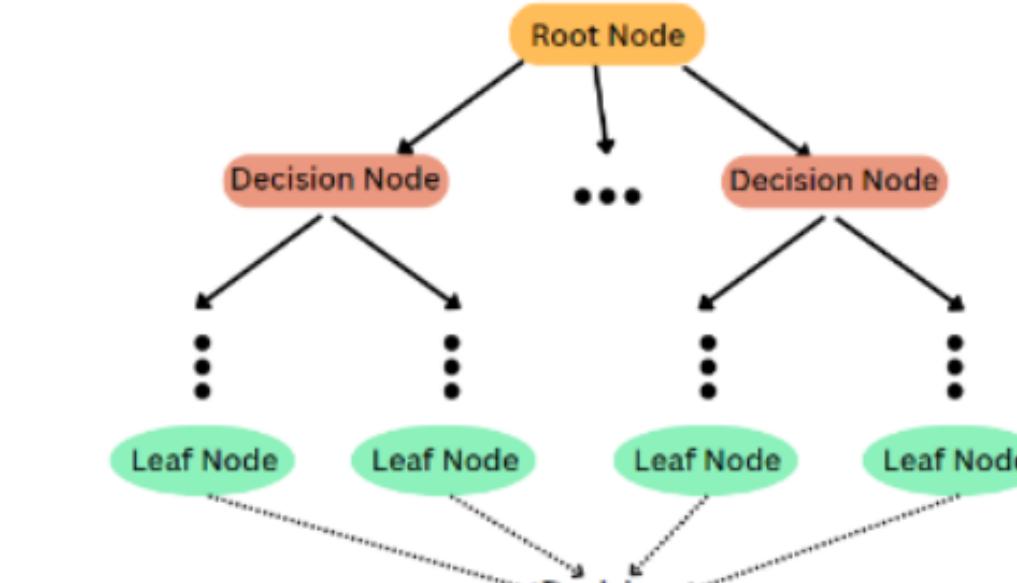
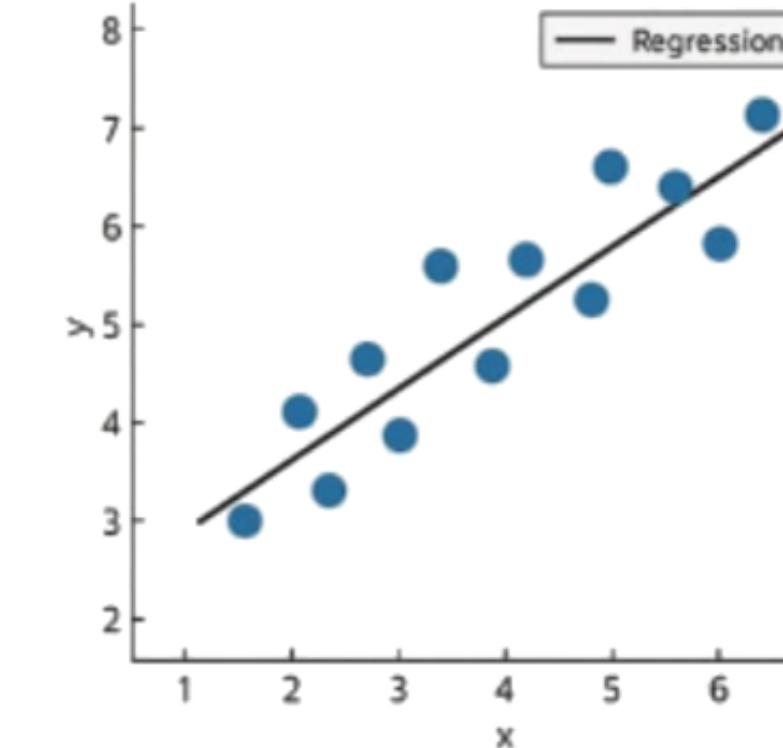
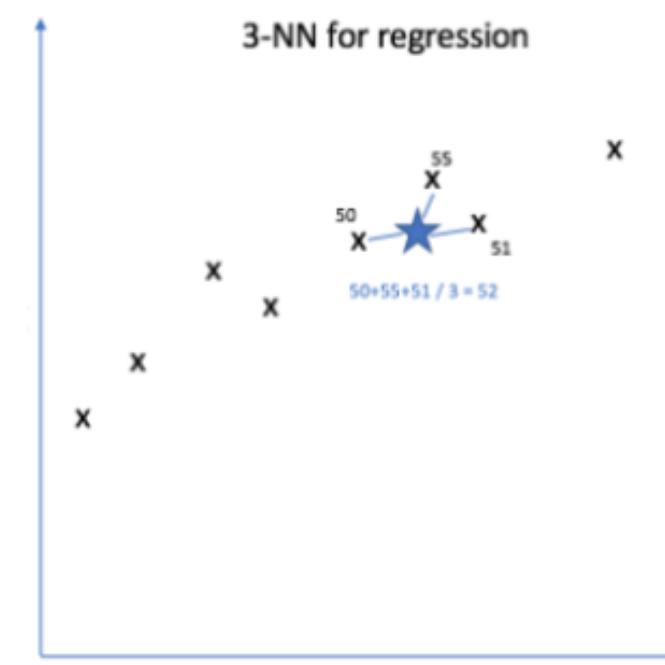
12156.556

**R<sup>2</sup>**



0.000 (Based on mean)

# Models In Consideration



Tree-Based

## **4. MODEL RESULTS:**

**THE BEST MODEL AND WHAT  
IT TELLS US**

# Performance Overview

Model	MAE	RMSE	R^2
Baseline	9132.437	12156.556	0
KNN Regressor	1272.606	4189.186	0.879
Linear Regression	4181.771	6063.585	0.75
Polynomial Regression	2870.173	4766.909	0.845
Ridge Regression	4182.268	6063.584	0.75
Lasso Regression	4182.846	6063.102	0.75
Decision Tree Regressor	607.44	2857.938	0.944
Random Forest Regressor	1235.035	2567.749	0.955
Gradient Boosting Regressor	1273.326	2635.217	0.952
Hist Gradient Boosting Regressor	1528.816	2784.487	0.947
XGBoost Regressor	643.087	2234.407	0.966

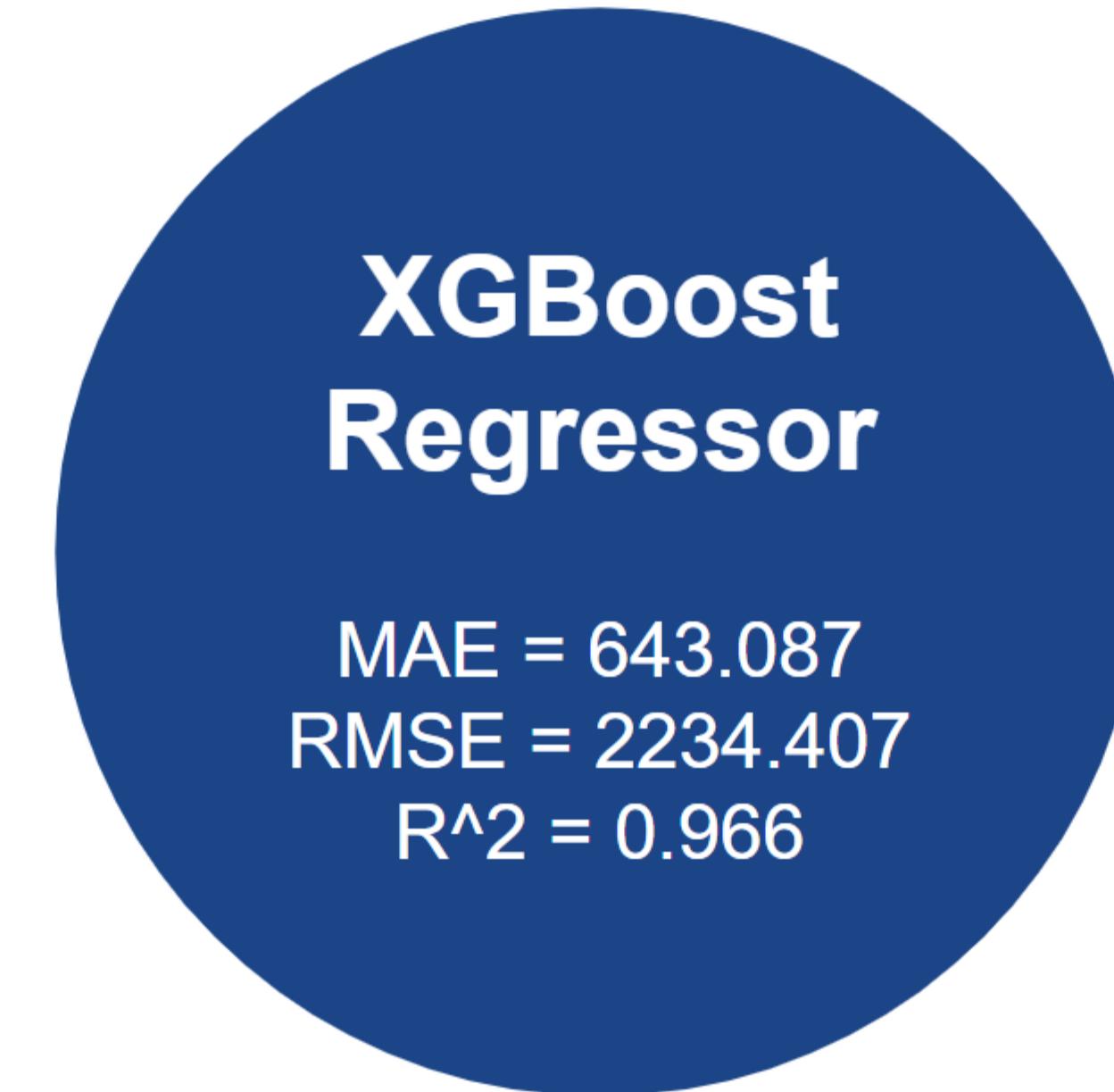
# Performance Overview: Best Model

## MAE

1. Decision Tree Regressor
2. XGBoost Regressor\*
3. Random Forest Regressor

## RMSE

1. XGBoost Regressor\*
2. Random Forest Regressor
3. Gradient Boosting Regressor

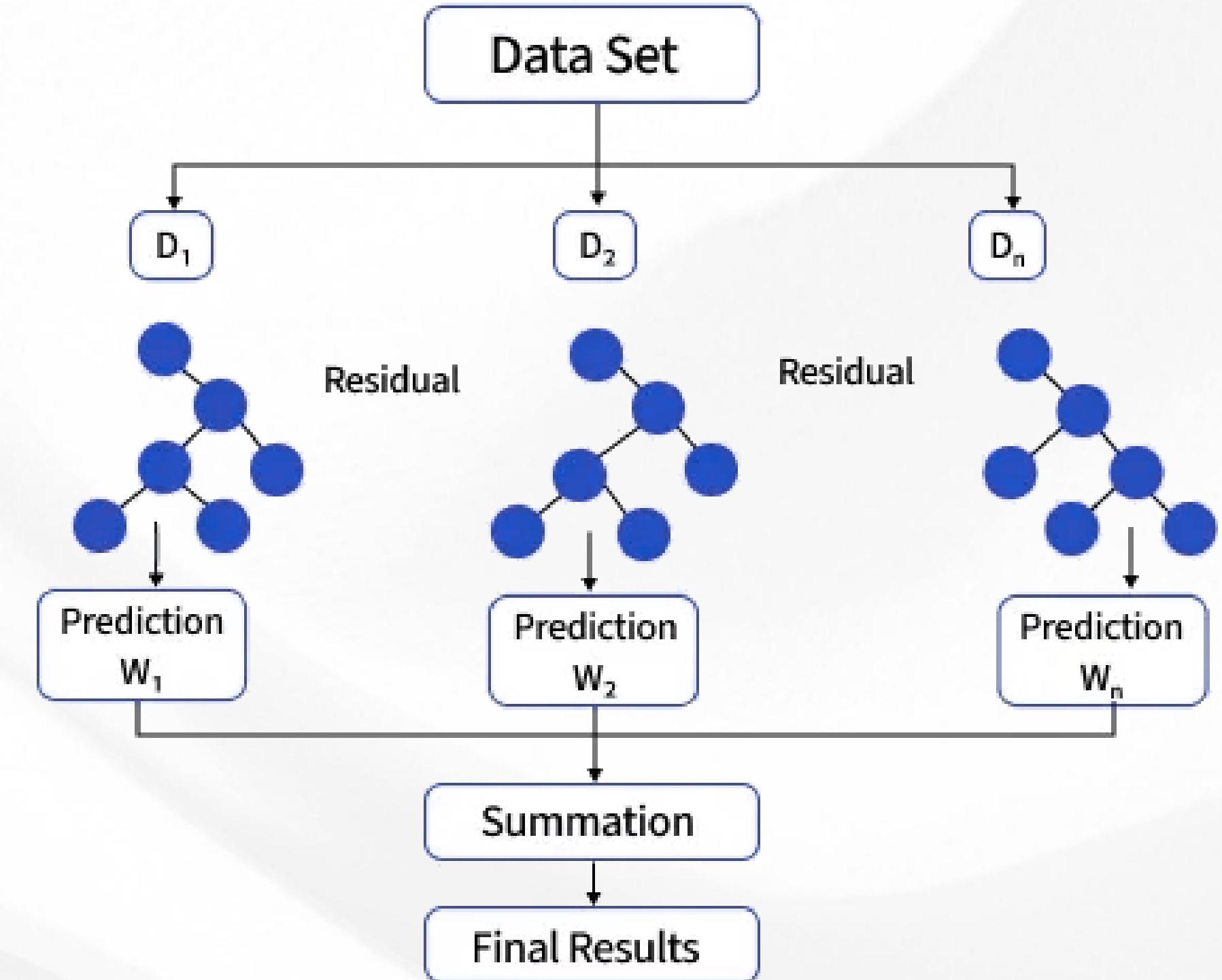


1. XGBoost Regressor\*
2. Random Forest Regressor
3. Gradient Boosting Regressor

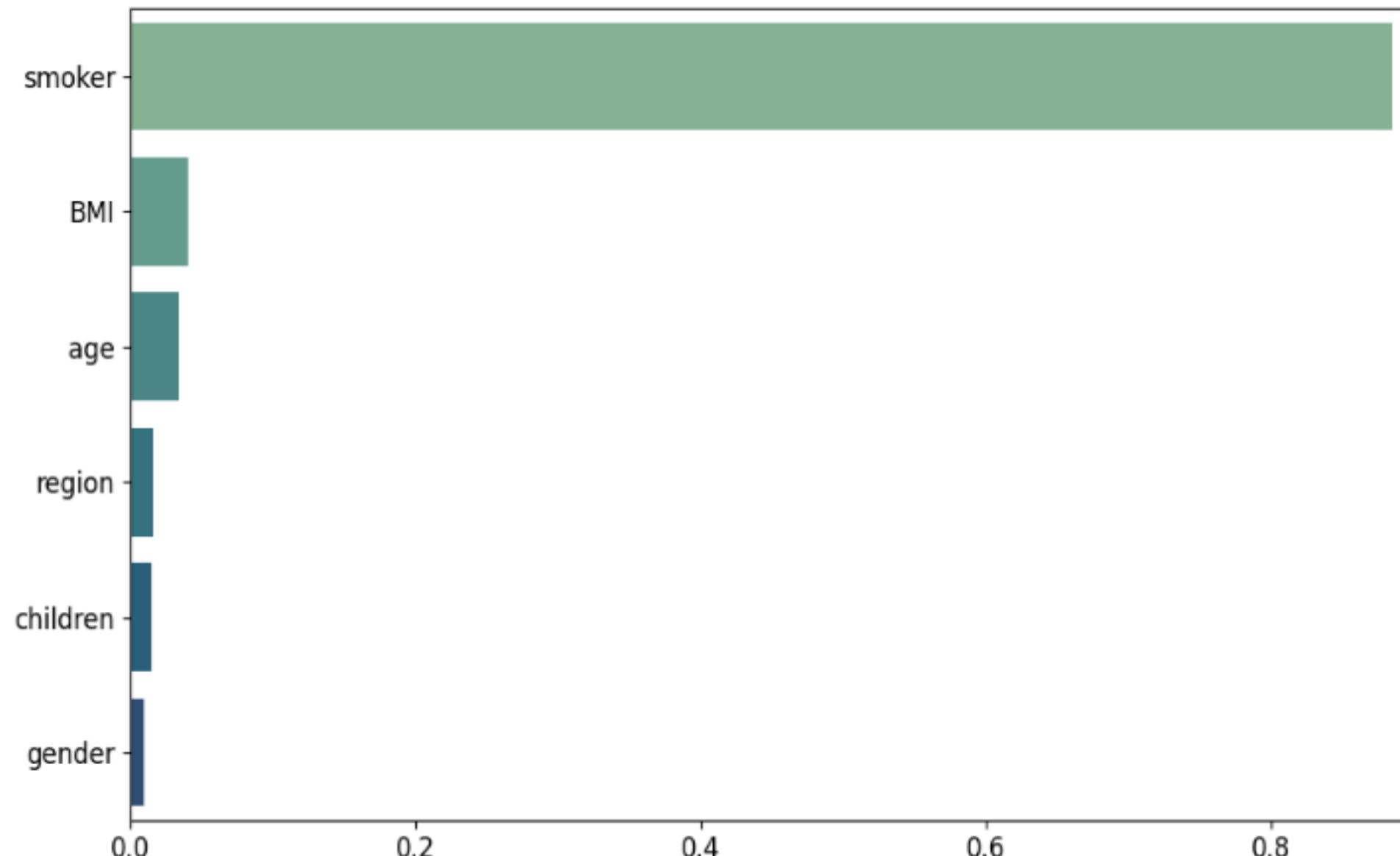
**$R^2$**

# Model Interpretation: XGBoost

- An ensemble model that sequentially creates decision trees derived from the errors of previous trees
- Prunes trees backwards after reaching minimum depth to maximize gain and reduce chances of overfitting
- Then factors in the predictions of all models together for a final decision



# Model Interpretation: XGBoost



## Most Important Features

Smoker - 88.85%  
BMI - 4.05 %  
Age - 3.43 %

## Least Important Features

Region - 1.585 %  
Children 1.49 %  
Gender - 0.941 %

## Why is Smoker so High?

**Real Life:** Smokers usually have drastically higher medical costs and premiums.

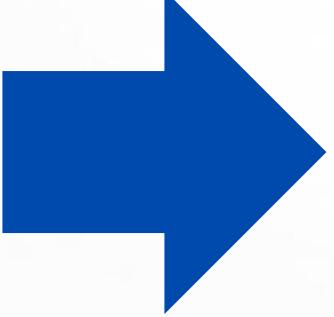
**Model:** XGBoost learns and builds more trees that split on Smoker first.

## **5. OUR FINDINGS:**

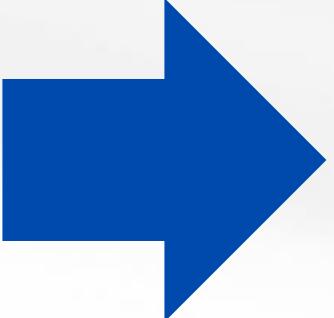
**APPLYING OUR MODEL AND  
WHAT PATIENTS CAN TAKE  
AWAY FROM THIS**

# Why Are Costs So High?

## Why the Numbers Look High

- 
- Dataset reflects total medical insurance costs billed to beneficiaries
  - Explains why some individuals exceed **\$50,000** in annual charges
  - Average one-night stay at a U.S. hospital exceeds **\$3,000**

## Context From National Data

- 
- Avg. employer-sponsored premium (2024): **\$8,951** for single coverage
  - Smoking-related illnesses add over **\$100 Billion** in direct U.S. healthcare costs annually

# Dominant Driver in Insurance Costs

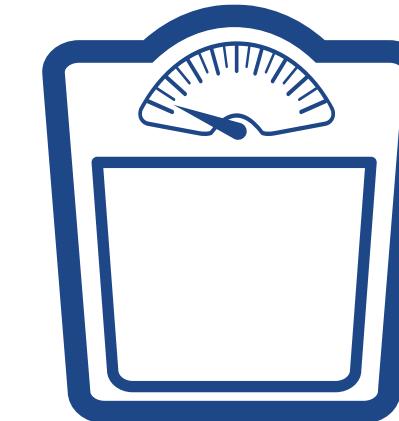
Age



Smoking



Obesity



The single strongest determinant of insurance price is smoking

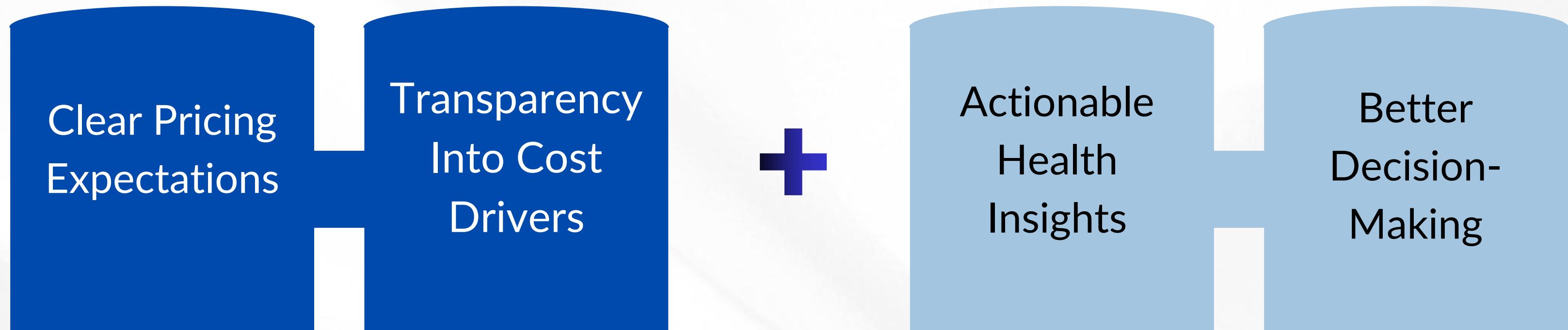
Sample_ID	Mock_Name	Original_Smoker_Status	Predicted_Non_Smoker_Price	Predicted_Smoker_Price	Price_Increase_If_Smoker
1362	Ole	0	\$8,965.83	\$19,895.90	\$10,930.07
2543	Reid	0	\$4,530.18	\$17,303.95	\$12,773.77
2229	Michael	0	\$11,731.44	\$23,315.32	\$11,583.88
2048	Ryan	0	\$3,945.26	\$33,153.18	\$29,207.92
446	Damian	0	\$4,685.57	\$39,034.12	\$34,348.55

# Practical Applications of Our Model

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- 1.** Consumers can input their own health characteristics to see an **approximate cost**.
- 2.** If insurer quotes differ dramatically from model predictions, users can flag or **investigate discrepancies**.
- 3.** Helps individuals **anticipate future insurance expenses**.

# How This Will Help Consumers?



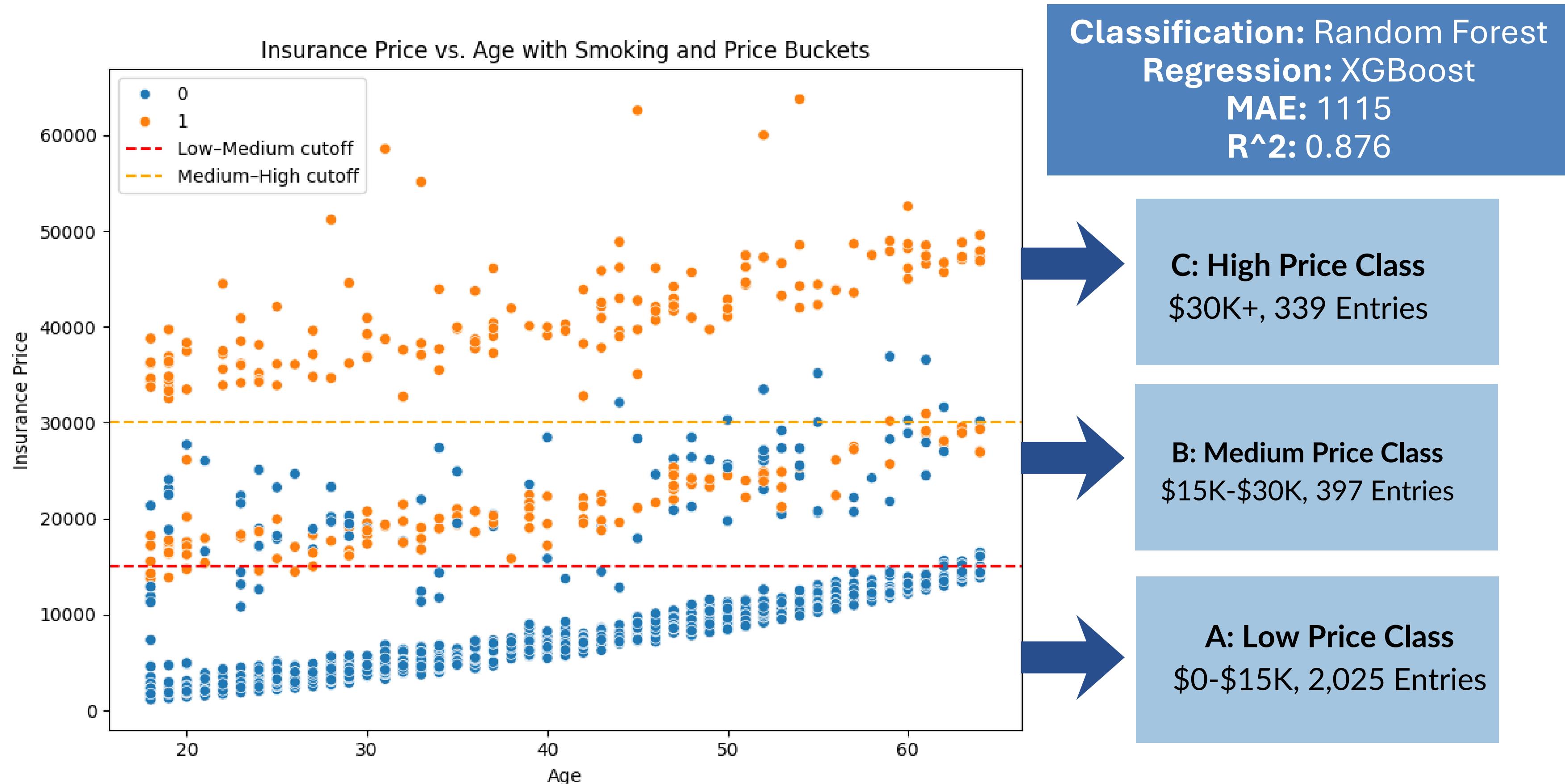
Pricing Clarity

Health Impact

**BONUS:**

**THE CUTTING ROOM FLOOR  
(AND POTENTIAL IMPROVEMENTS)**

# Two Stage Approach Classification into Regression



**Thank You!**

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**Any Questions?**