# OPEN DATA SCIENCE CONFERENCE

#ODSC

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Boston | May 1 - 4 2018

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# Bayesian Hierarchical Model for Predictive Analytic

Amir Meimand
Director of R&D, Pricing Science, Zilliant

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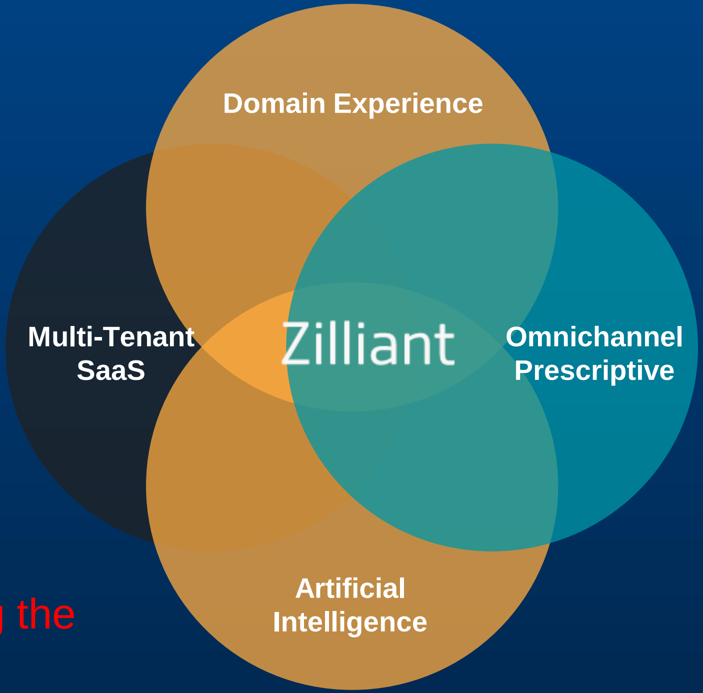
# About Zilliant

- Founded in 1998
- Headquartered in Austin, Texas
- 200 employees & contractors
- Serving B2B Distribution, Manufacturing & Industrial Services
- 120+ customers around the world. 100’s of implementations
- Investors: ABS Ventures, Houston Ventures, Trellis Partners,
- and Goldman Sachs




The world’s leading AI-enriched SaaS platform for maximizing the lifetime value of B2B customer relationships.

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# About Zilliant

## Zilliant IQ

Converting Strategic Insights into Account Specific Action Plans

### Ex. Data In

- Product Master
- Customer Master
- Transaction Data
- Win / Loss Data
- 3rd Party Data
- Competitor Price Data

### Zilliant IQ – Multi-Tenant SaaS Platform

Cloud Infrastructure: Highly Scalable – Secure – Collaborative – In-Memory Reporting

**Action IQ – Actionable Intelligence & Sales Guidance**

- Account Potential
- Account Health
- Dashboards & Collaboration
- Action Plans & Campaigns
- Quotes
- Agreements

**IQ Engines – AI & Prescriptive & On-Demand Insights**

- Cart IQ
- Cost IQ
- Price IQ
- Profit IQ
- Sales IQ

**Zilliant IQ Anywhere – Integration & Omnichannel Activation**

### Omnichannel Activation

Zilliant Apps.

- Email
- Mobile
- Browser

Enterprise Integration…

- CRM / CPQ
- eCom
- Quoting Tools
- ERP

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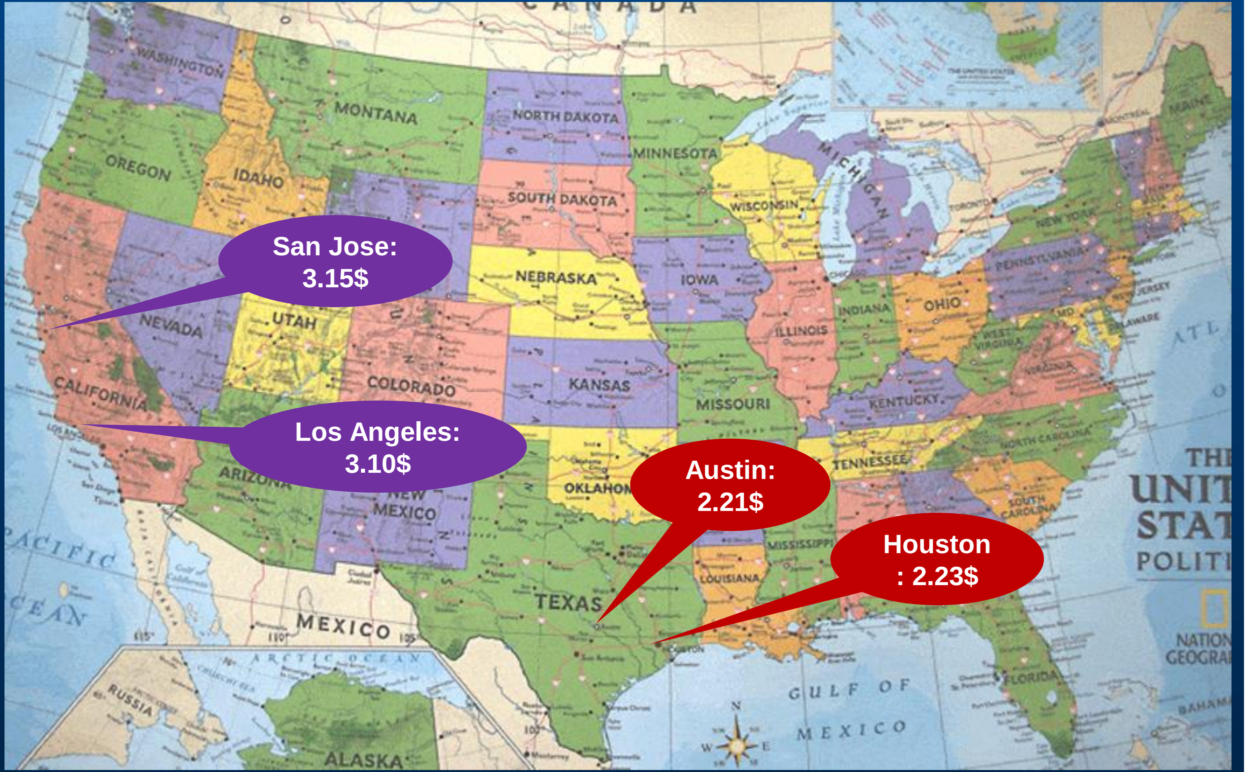
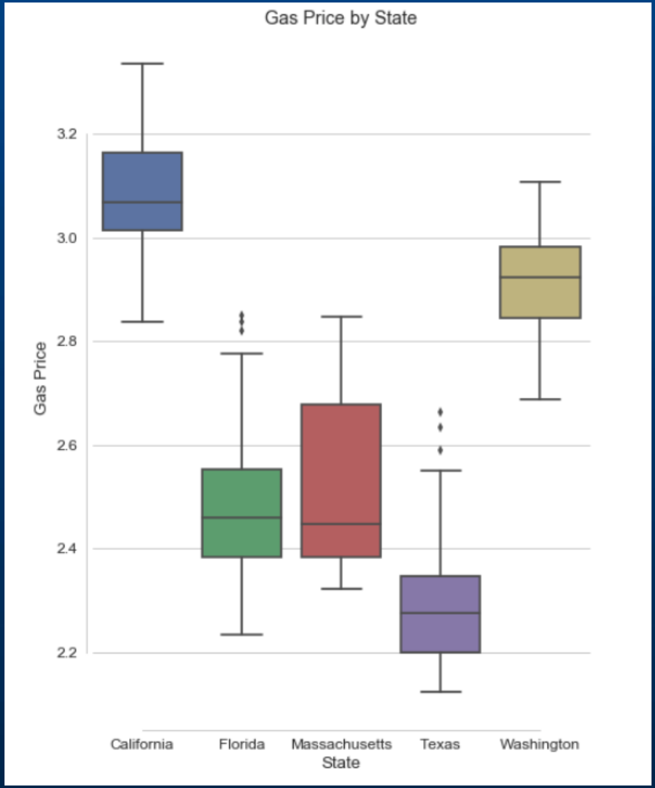
# Gas Price:

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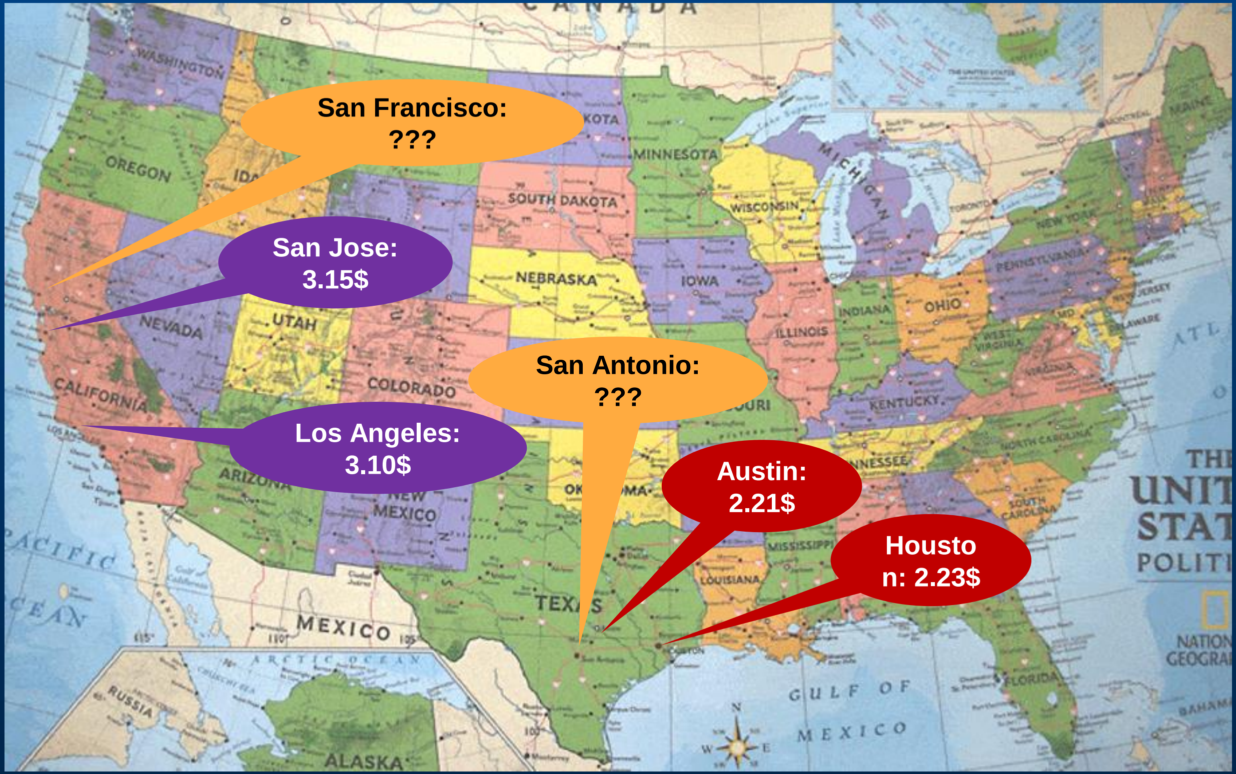
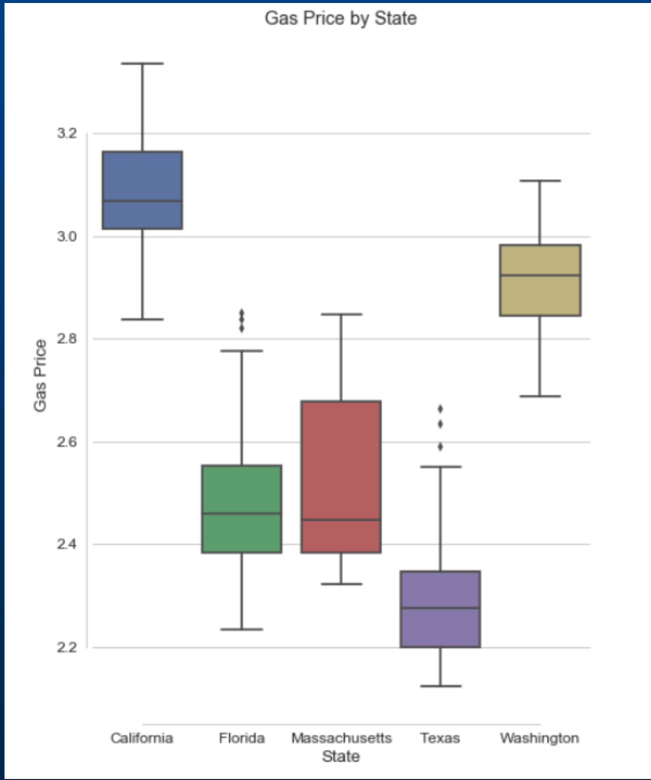
Source: https://www.eia.gov

# Gas Price:

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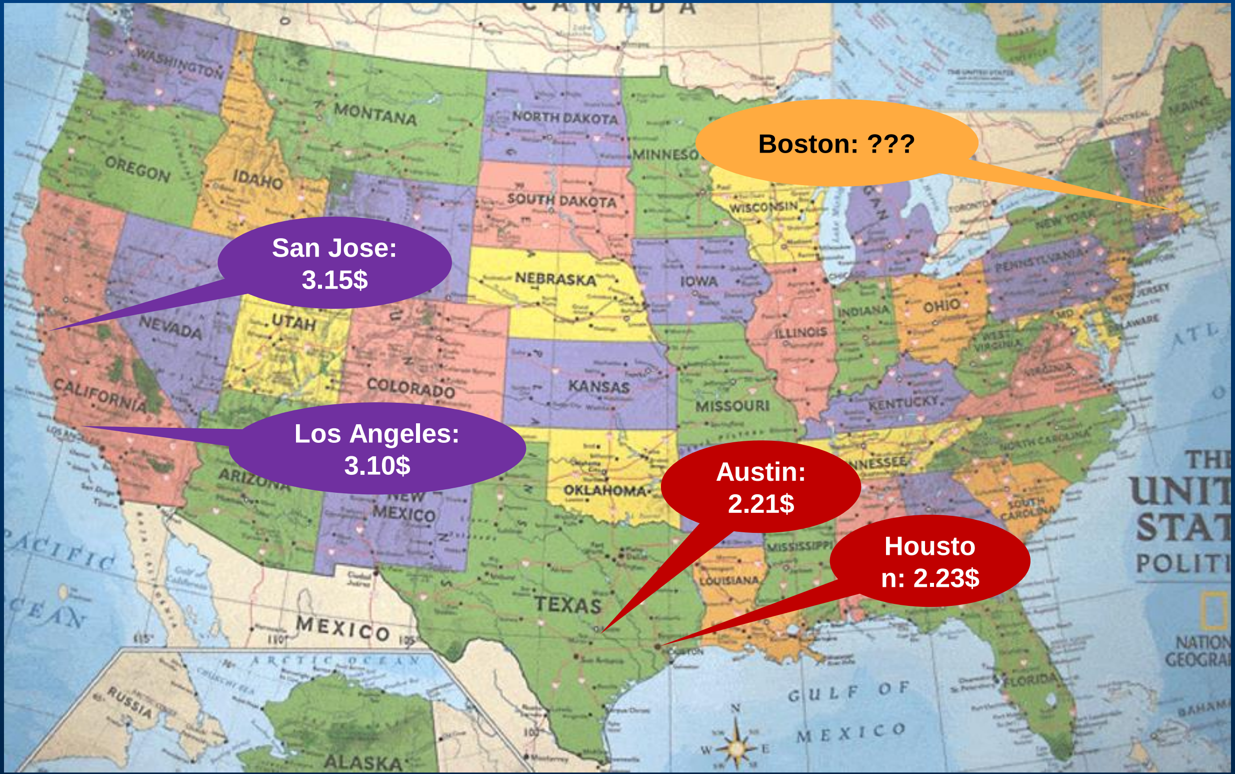
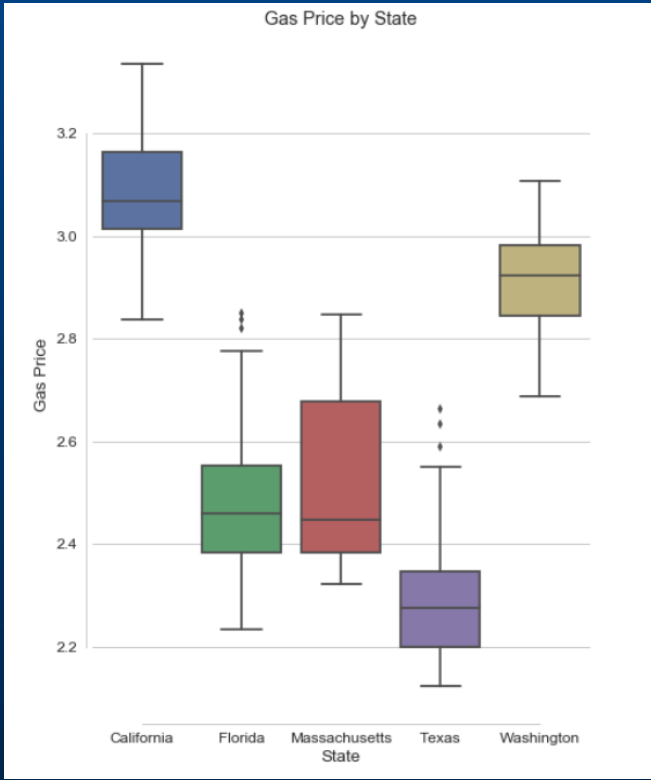
Source: https://www.eia.gov

# Gas Price:

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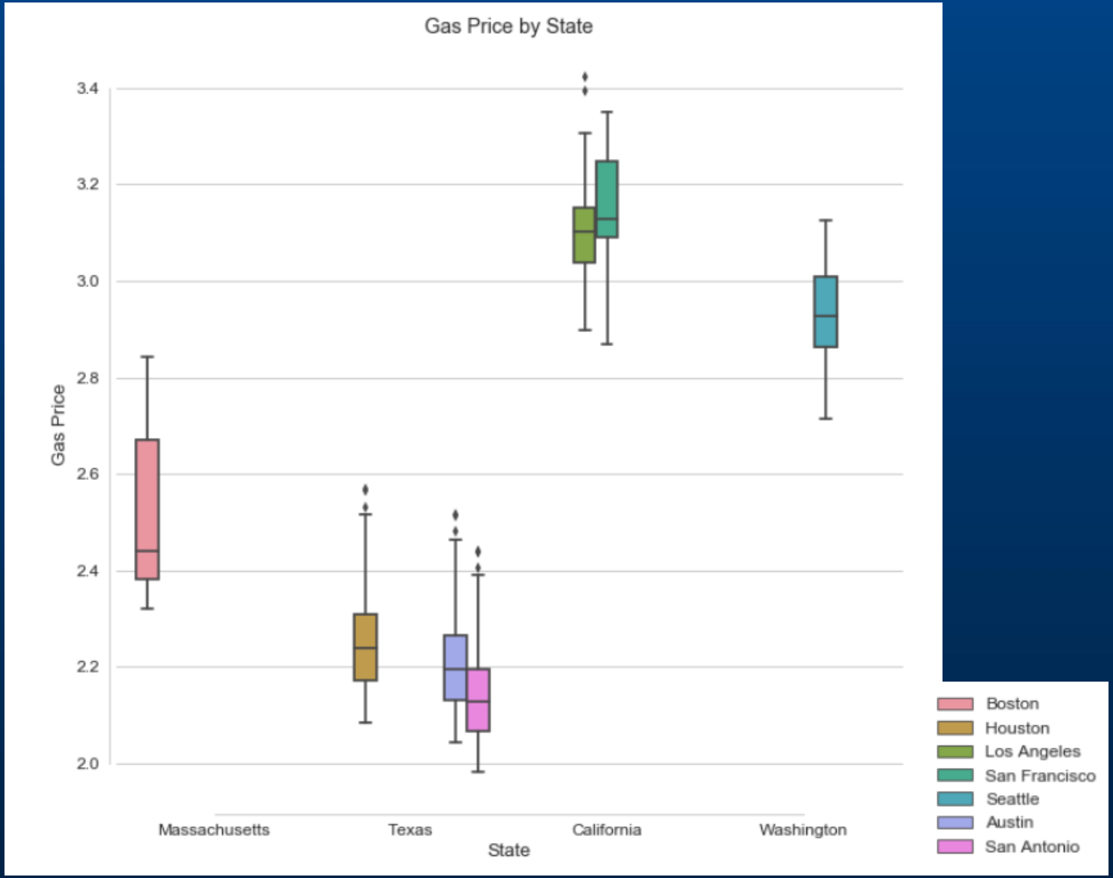
Source: https://www.eia.gov

# Gas Price:




Source: https://www.eia.gov

# Gas Price:


San Antonio:

- Station 1: 3.5$
- Station 2: 3.8$

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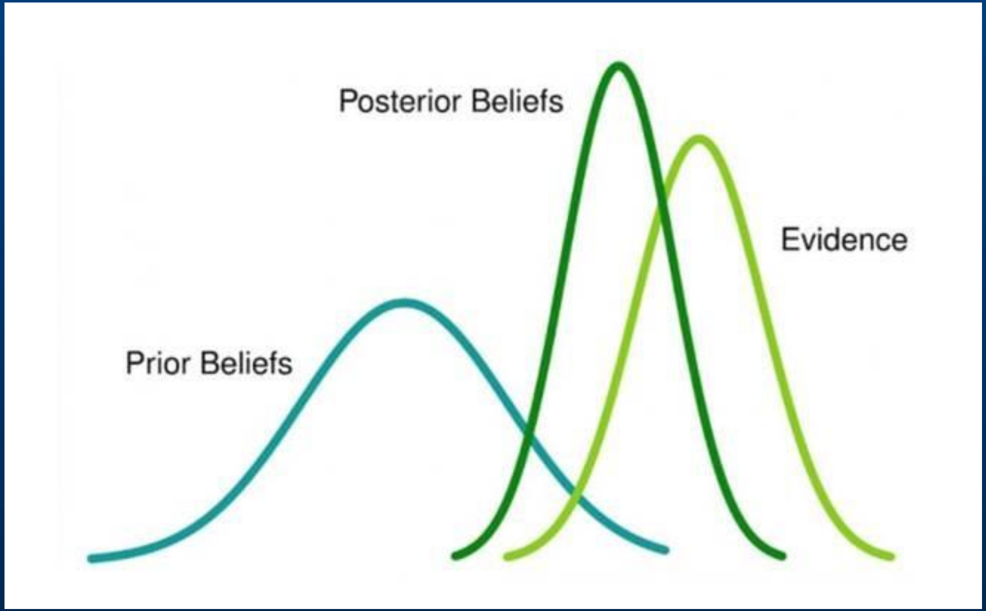
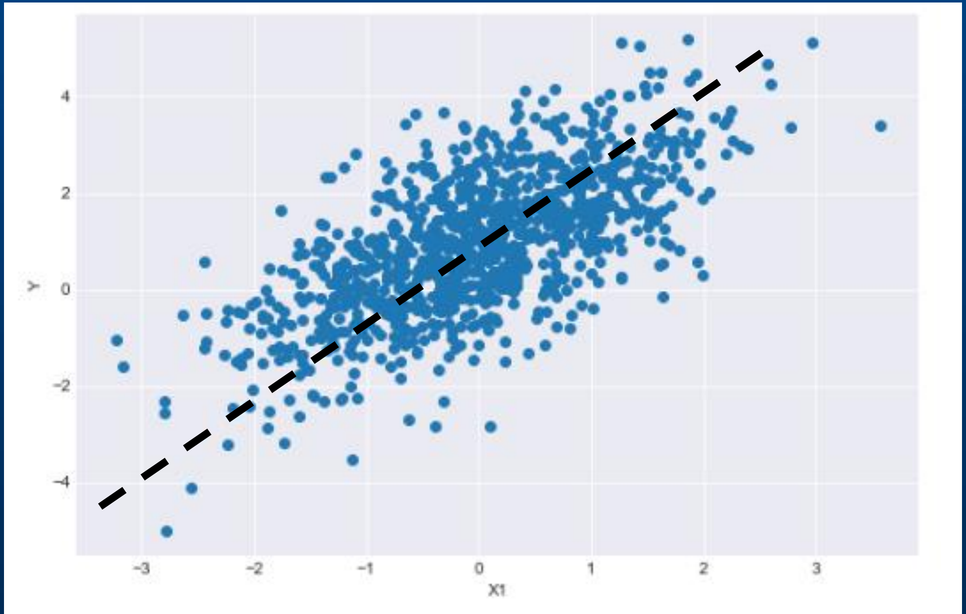
Source: https://www.eia.gov

# Bayesian Models



# Bayesian Regression




Assumed relationship: $y = \alpha + \beta x$

Priors: $\alpha \sim N(0, 10)$

$\beta \sim N(1, 5)$

**What other assumption(s) we have?**

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# Bayesian Regression

1- What is the target variable? **Y which depends on Alpha and Beta**

2- What is assumed (potential distribution)? **Normal Distribution**

3- Define priors **Alpha and/or Beta distribution**

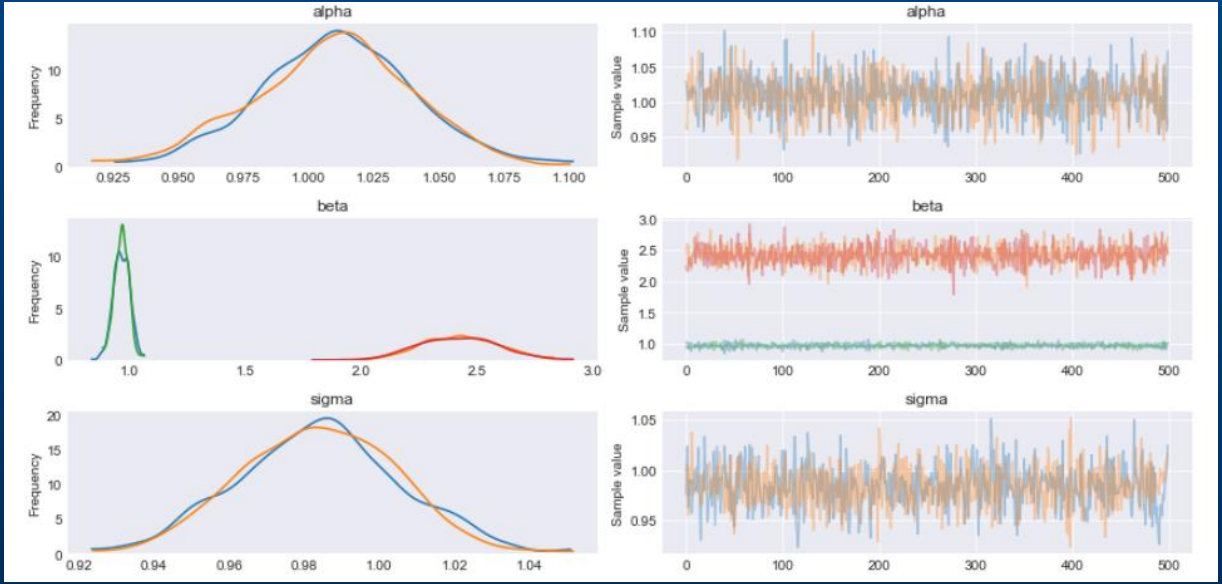
# Bayesian Regression

```
regression_model = pm.Model()

with regression_model:


    alpha = pm.Normal('alpha', mu=0, sd=10)
    beta = pm.Normal('beta', mu=1, sd=5)
    sigma = pm.HalfNormal('sigma', sd=1)


    mu = alpha + beta*X1


    Y_obs = pm.Normal('Y_obs', mu=mu, sd=sigma, observed=Y)
```

***Create stochastic variables***

***Create deterministic variable***

# Bayesian Regression

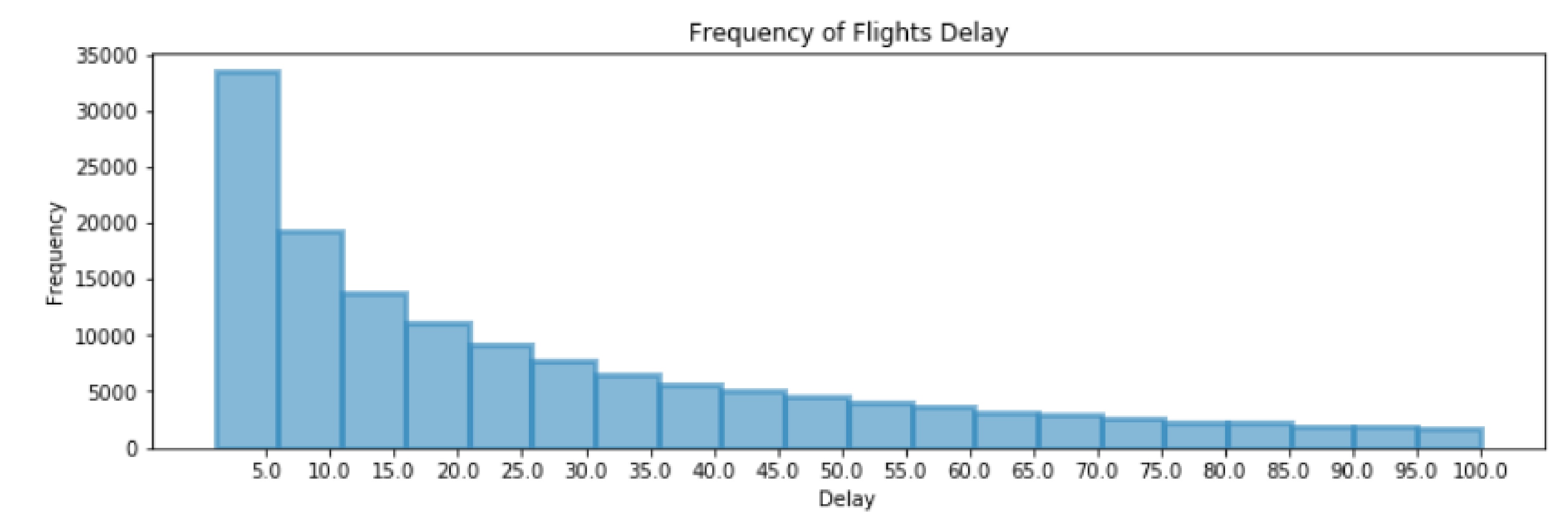



| | mean | sd | mc_error | hpd_2.5 | hpd_97.5 | n_eff | Rhat |
|---|---|---|---|---|---|---|---|
| alpha | 1.009507 | 0.029933 | 0.000790 | 0.950972 | 1.065191 | 1515.745188 | 1.000558 |
| beta__0 | 0.967910 | 0.032986 | 0.000856 | 0.905172 | 1.032044 | 1451.511508 | 0.999007 |
| beta__1 | 2.420182 | 0.164576 | 0.004431 | 2.120133 | 2.747157 | 1641.803594 | 0.999708 |
| sigma | 0.983615 | 0.021083 | 0.000603 | 0.945488 | 1.024915 | 1201.344314 | 0.999019 |

# Flight Delay Prediction

# Flight Delay Prediction:

## Evidence (IAH Airport)

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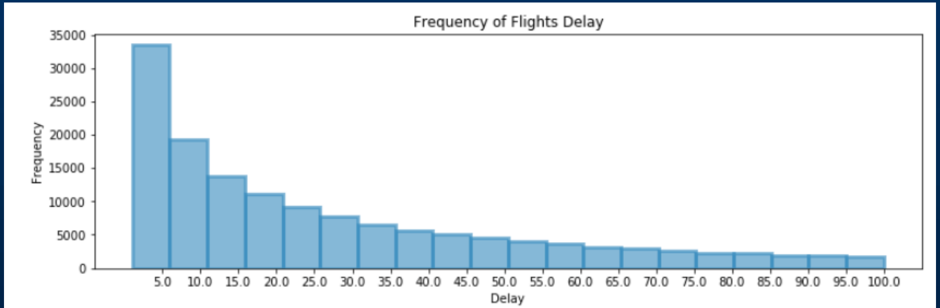
Source: http://stat-computing.org/dataexpo/2009/the-data.html

# Modeling Step

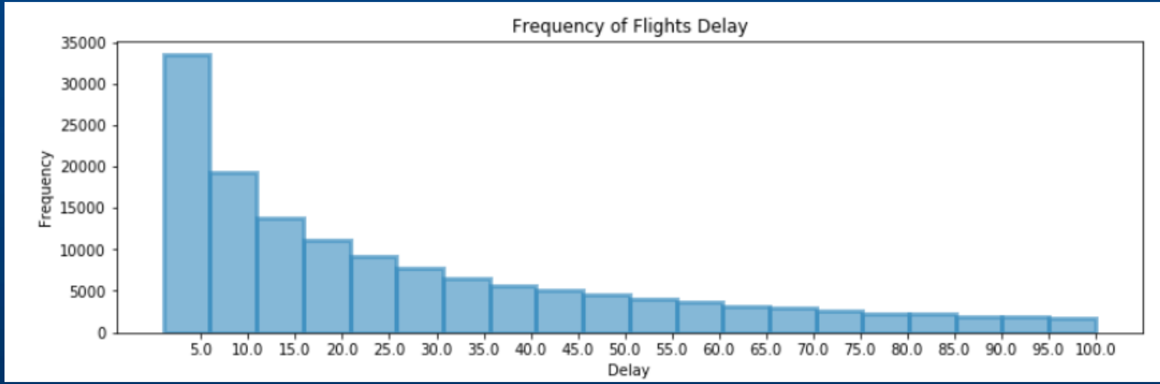
1- What is the target variable?

2- What is assumed (potential distribution)?

3- Define priors

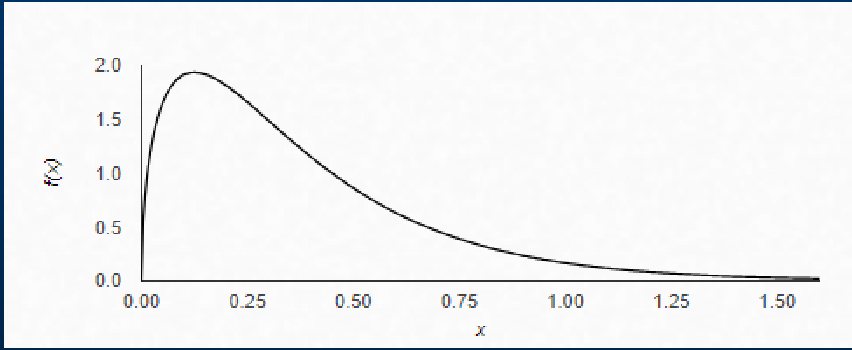


# Flight Delay Prediction:




**Evidence (IAH Airport)**

$$f(x;\lambda) = \lambda e^{-x\lambda}$$




**Prior Belief**

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Source: http://stat-computing.org/dataexpo/2009/the-data.html

# Flight Delay Prediction:

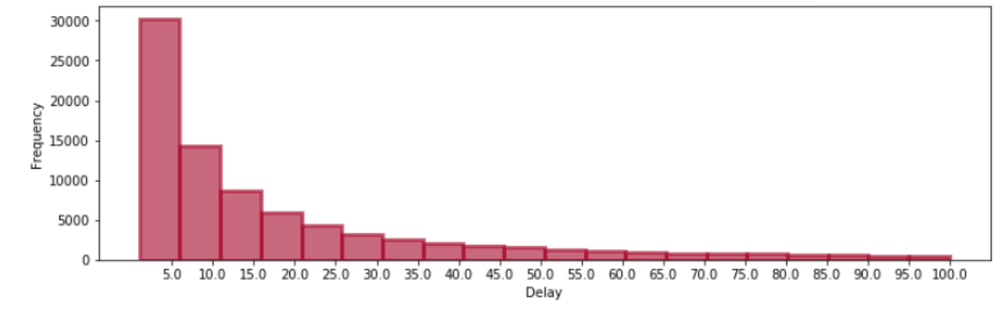
```
Flight_Delay = pm.Model()

with Flight_Delay:
    # Prior Distribution

    rate = pm.Gamma('rate', 2, 2)

    # Likelihood (sampling distribution) of observations
    Y_obs = pm.Exponential('Y_obs', rate, observed=x)
```

Prior Distribution of target variable

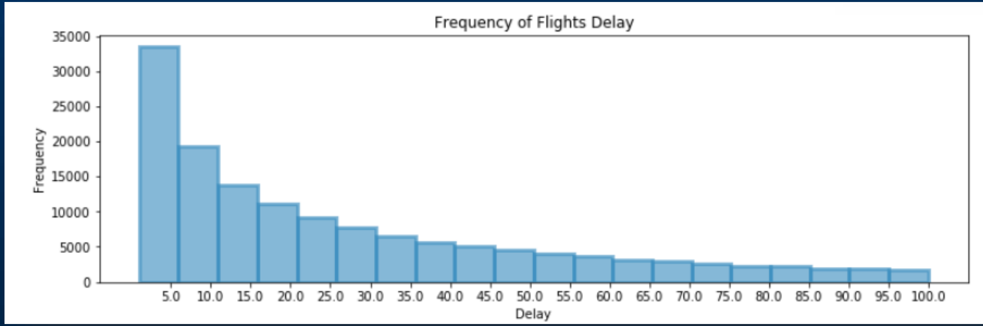
Relationship between

# Flight Delay Prediction:

## Evidence (ORD Airport)




## Evidence (IAH Airport)

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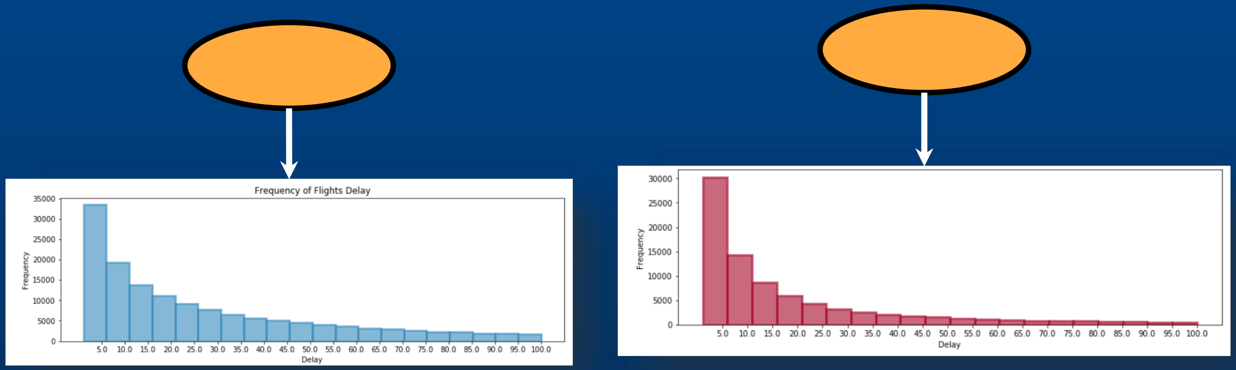
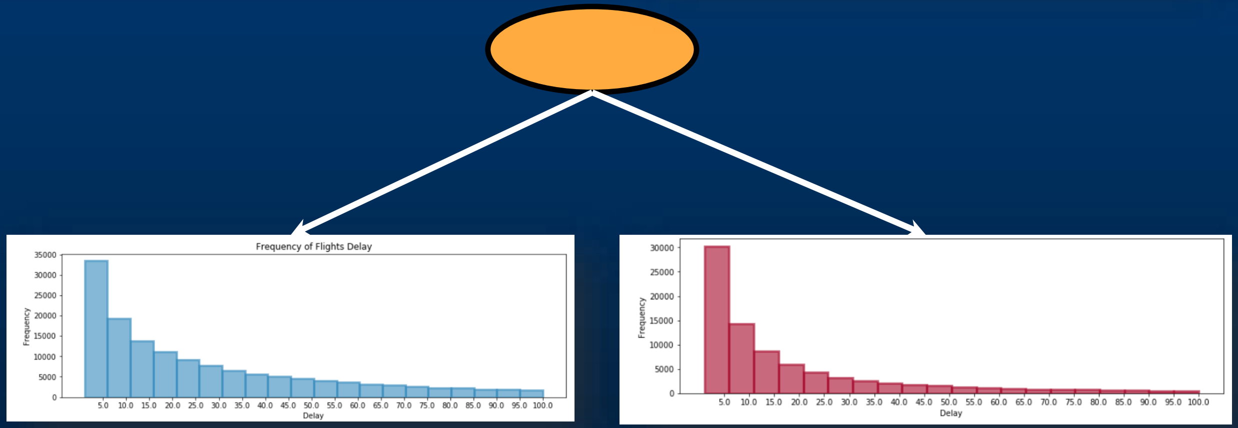
# Flight Delay Prediction:

**Every one has its own model!**




**All have one model!**

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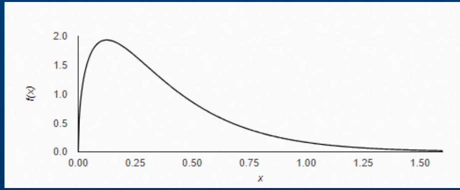
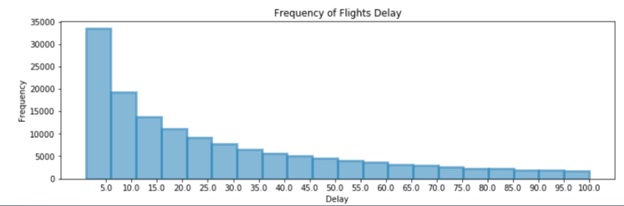
# Flight Delay Prediction:

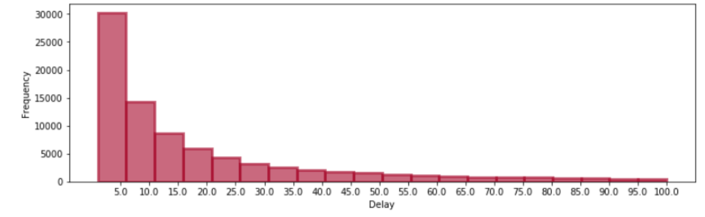
$$Gamma(\alpha_1, \beta_1)$$




$$f(x; \lambda_1) = \lambda_1 e^{-x\lambda_1}$$




$$f(x; \lambda_2) = \lambda_2 e^{-x\lambda_2}$$



# Flight Delay Prediction:

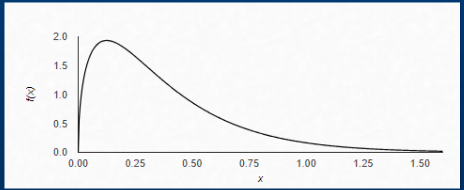
```
Flight_Delay = pm.Model()

with Flight_Delay:
    # Prior Distribution
    rate = pm.Gamma('rate', alpha, beta,shape=2)


    rate_hat=rate[airport]
    # Likelihood (sampling distribution) of observations
    Y_obs = pm.Exponential('Y_obs', rate_hat, observed=Delay)
```

# Flight Delay Prediction:

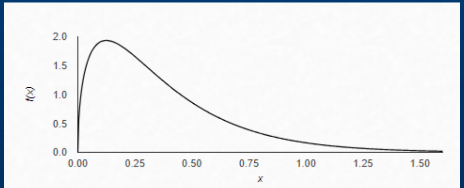
$$\alpha_1, \alpha_2 \sim N(\mu_1, \sigma_1)$$

$$\beta_1, \beta_2 \sim N(\mu_1, \sigma_1)$$

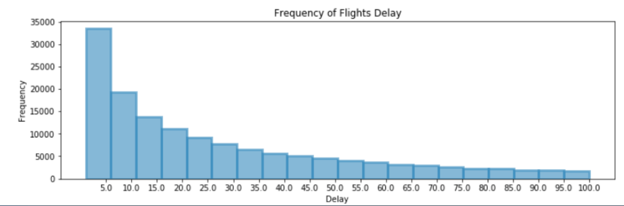
$$Gamma(\alpha_1, \beta_1)$$



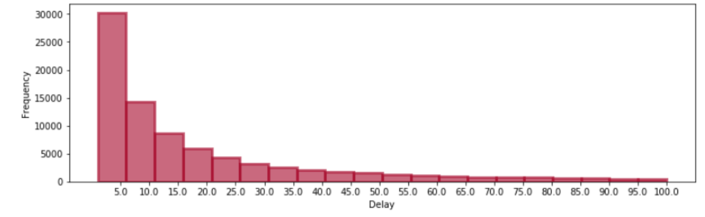

$$Gamma(\alpha_2, \beta_2)$$




$$f(x; \lambda_1) = \lambda_1 e^{-x\lambda_1}$$




$$f(x; \lambda_2) = \lambda_2 e^{-x\lambda_2}$$

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# Flight Delay Prediction:

```
Delay = z1.DepDelay.values

Flight_Delay = pm.Model()

with Flight_Delay:
    # Prior Distribution
    alpha = pm.Normal('alpha', mu=2, sd=5)
    beta = pm.Normal('beta', mu=2, sd=5)

    rate = pm.Gamma('rate', alpha, beta,shape=2)


    rate_hat=rate[airport]
    # Likelihood (sampling distribution) of observations
    Y_obs = pm.Exponential('Y_obs', rate_hat, observed=Delay)
```

# Artificial Intelligence – A Definition for B2B

**The capability of a machine to imitate intelligent human behavior**

**What if your best…**

**Sales Person**

**Pricer**

**Buyer**

**Product Manager**

**Financial Analyst**

**…could evaluate every customer relationship, every day and recommend action?**

**How would that impact customer lifespan, revenue and profit?**

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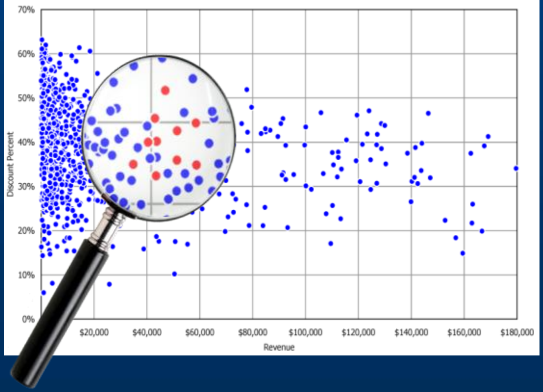
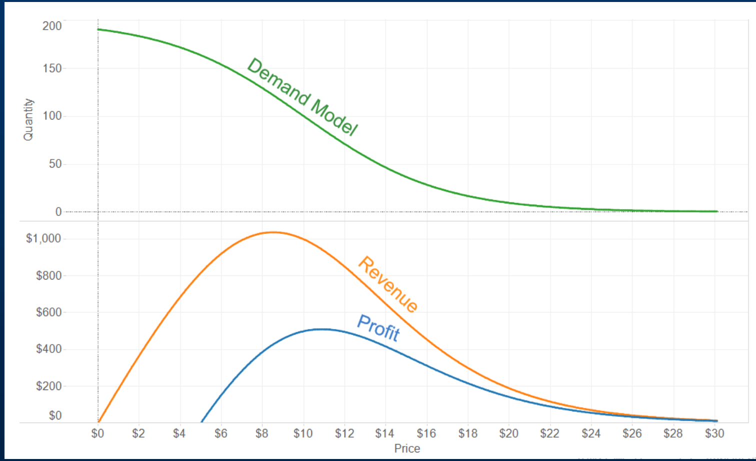
# Price Optimization

Machine learning for market segmentation, price sensitivity, and price optimization.

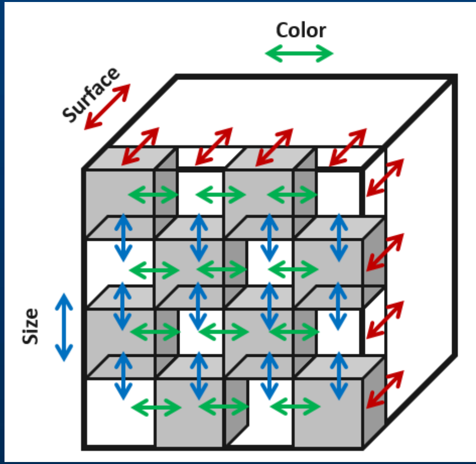
### Segment Clustering




### Convex Optimization




### Pricing Constraints

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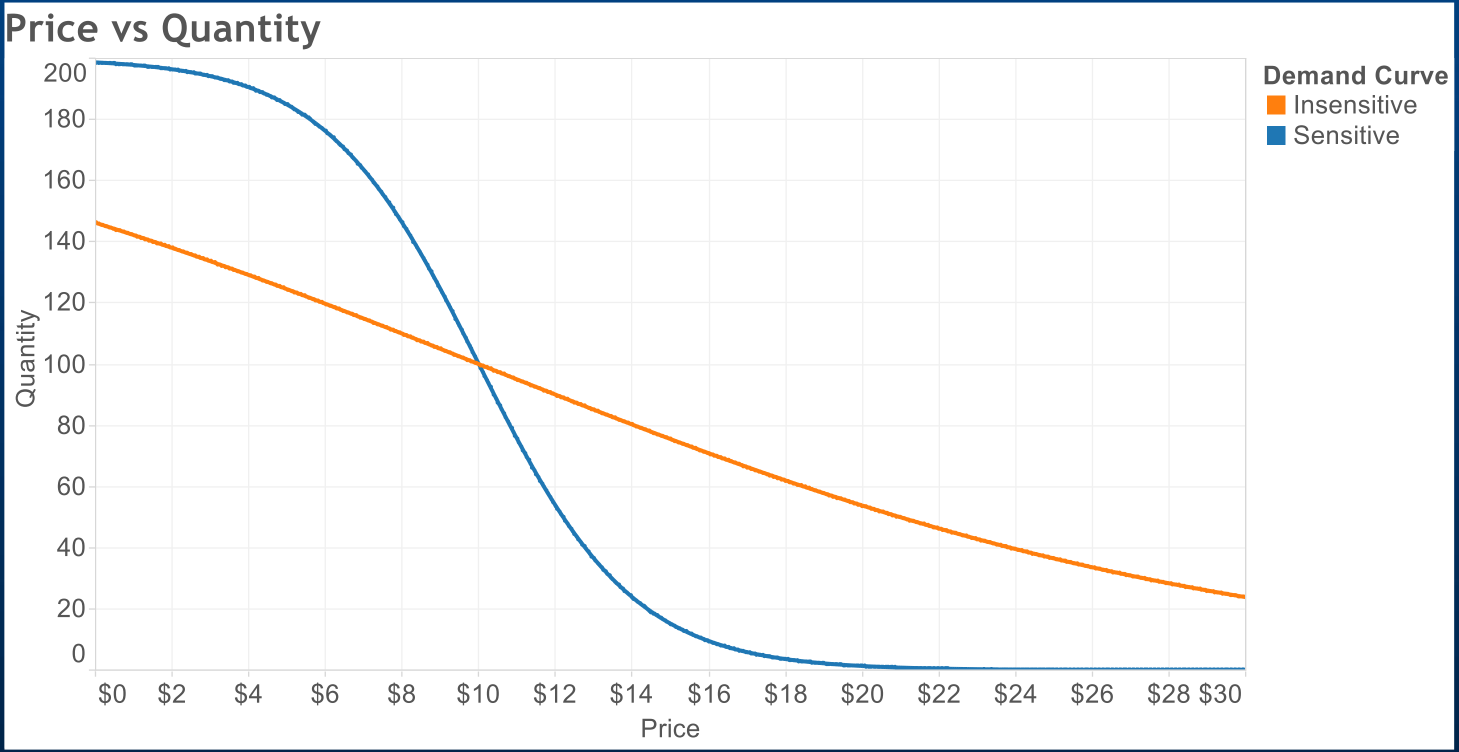
# Price Elasticity

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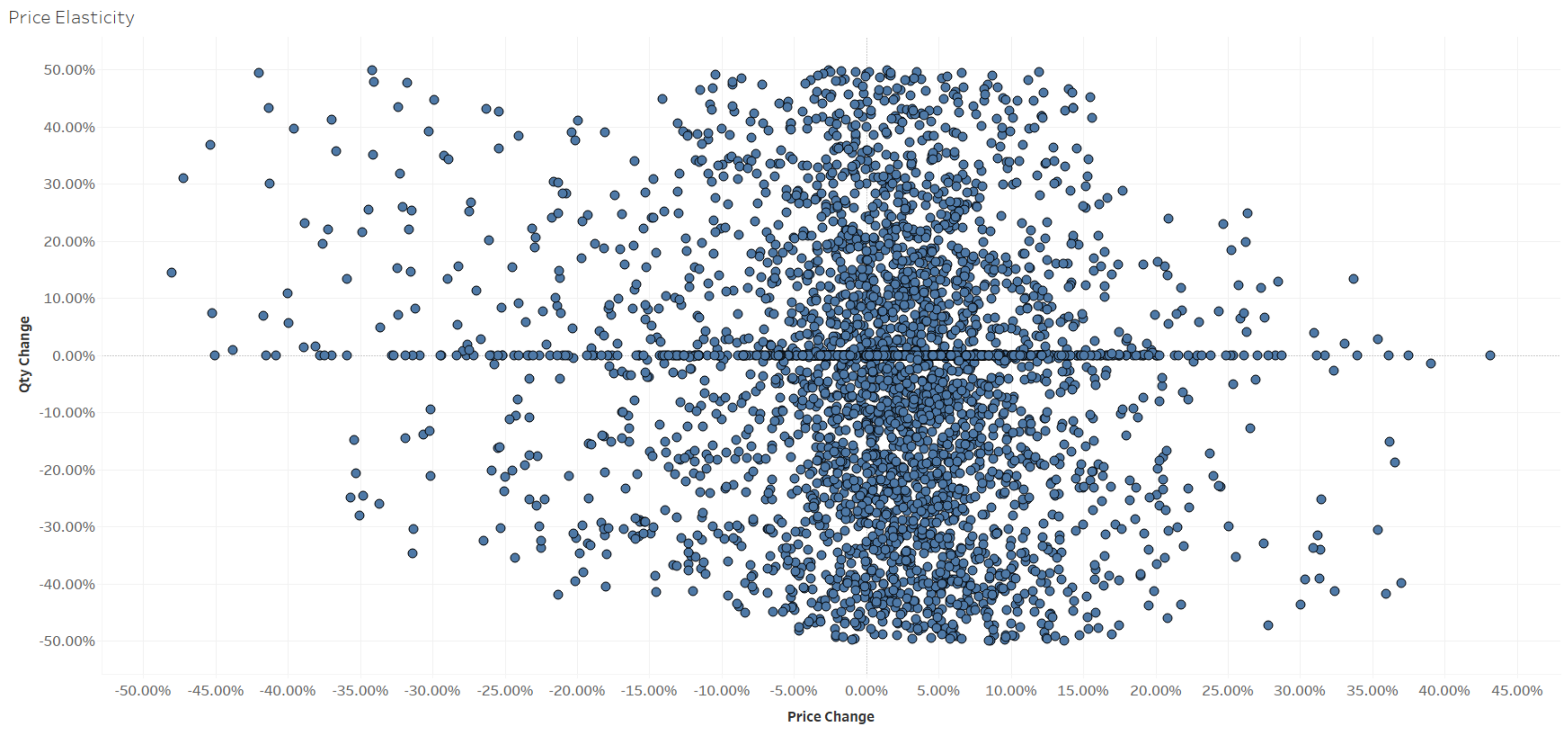
# What we hope to see (Dream)

# What we see (Reality!)

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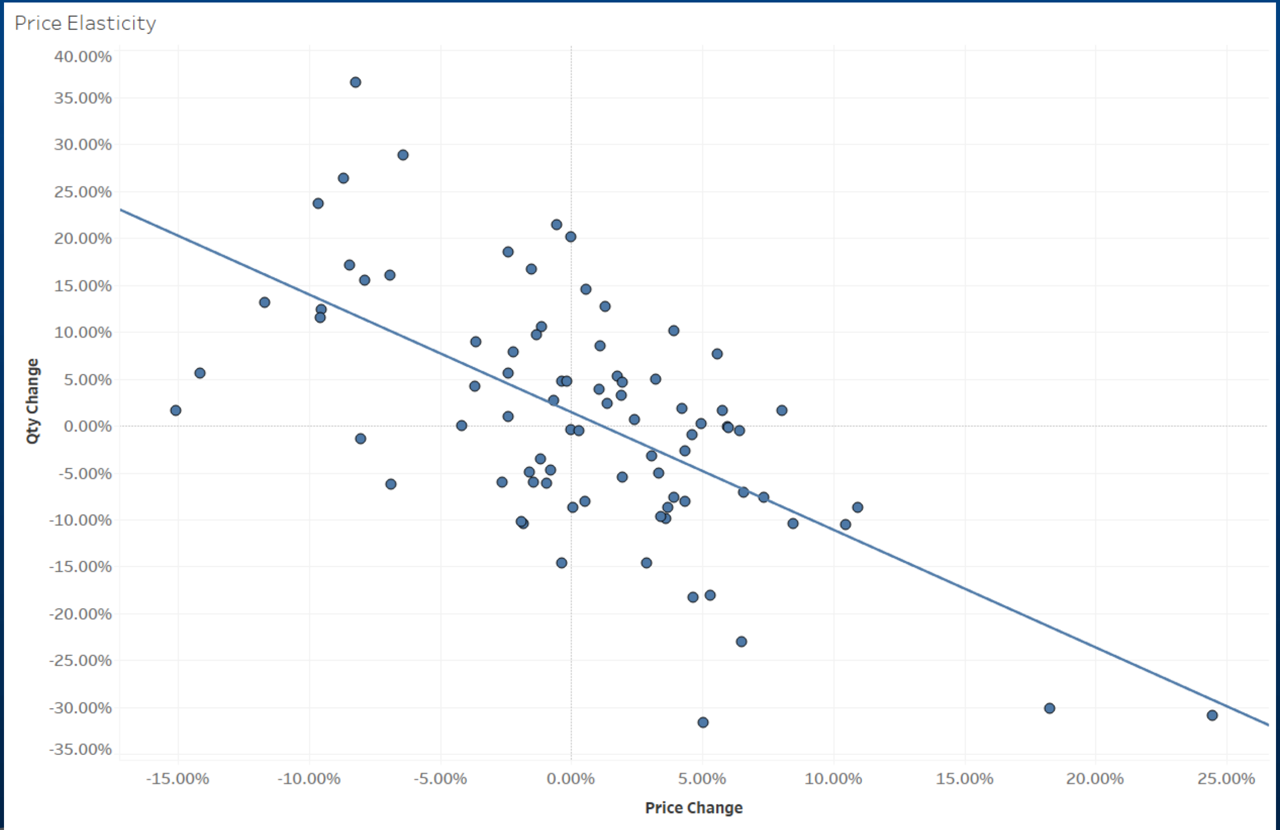
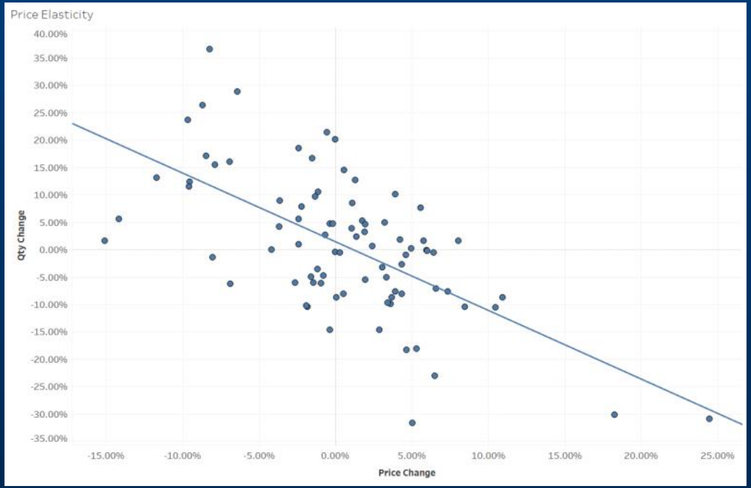
# Fix it!


Price Elasticity
40.00%
35.00%
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
-5.00%
-10.00%
-15.00%
-20.00%
-25.00%
-30.00%
-35.00%
Qty Change
-15.00%
-10.00%
-5.00%
0.00%
5.00%
10.00%
15.00%
20.00%
25.00%
Price Change

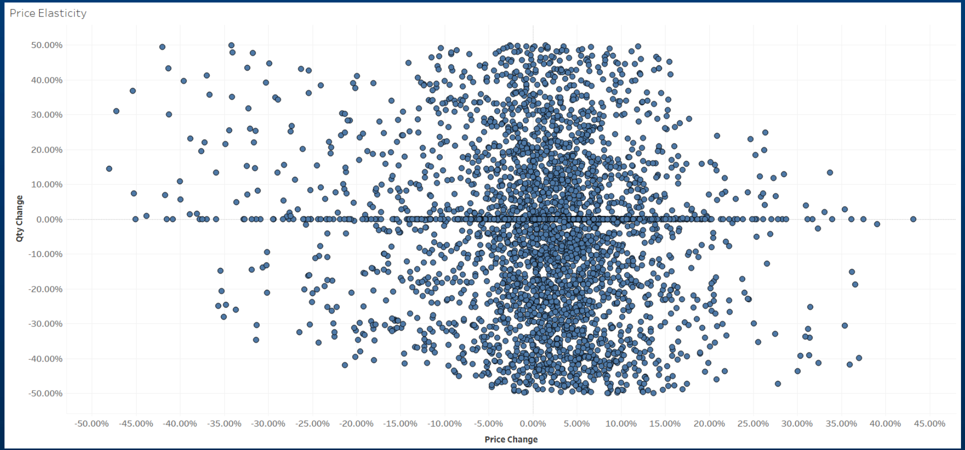
# Why Hierarchical Model?

**Clean Data, Less Data Points**




**Vs.**

**Noisy Data, Many Data Points**

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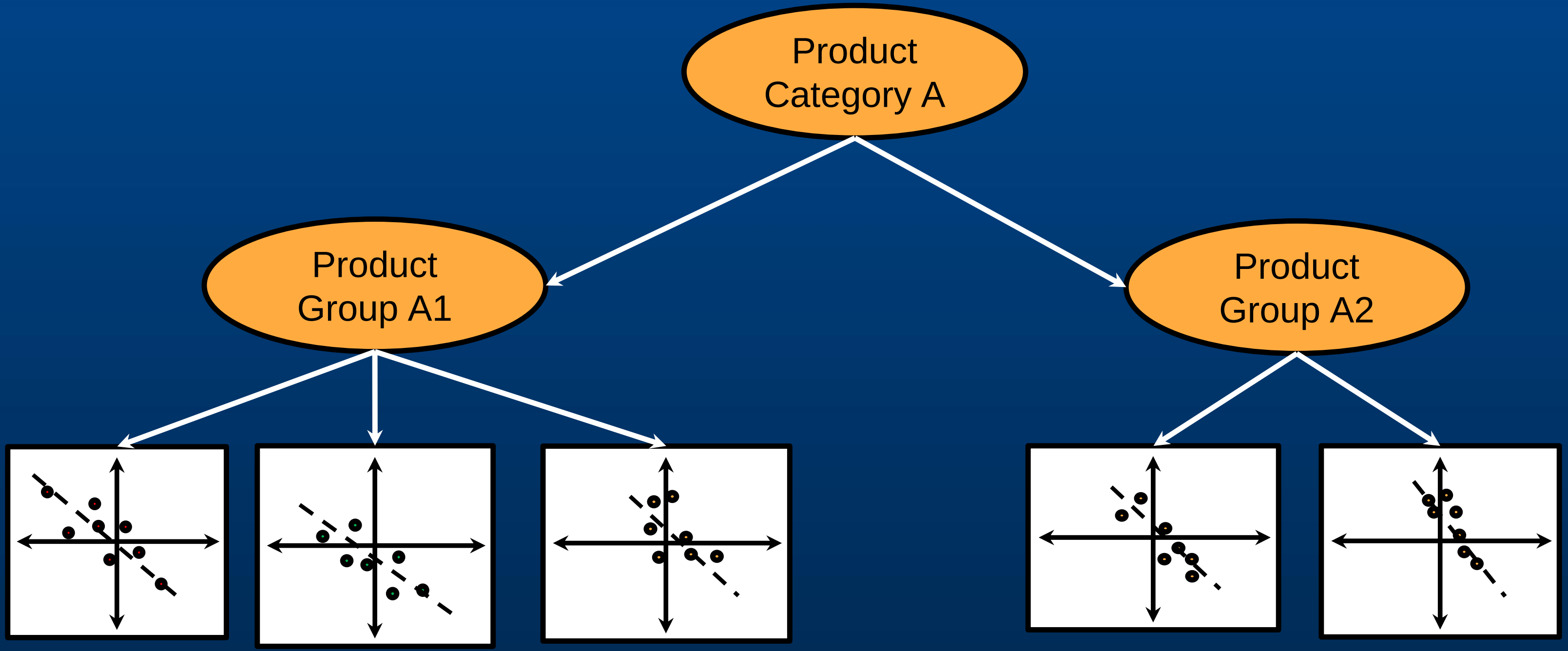
# Why Hierarchical Model?

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# Zilliant ML Platform (Point and Click!)

## Step 1- Define Hieratical Levels

**Segmentation Trees: PSE**

Segmentation Tree Name: PSE

Purpose: Time-Based Metrics

**Segmentation Tree Levels**

| Use | Order | Attribute | Entity |
|---|---|---|---|
| ☑ | 0 | zProduct_Id | Transaction |
| ☑ | 1 | Customer_Program | Transaction |
| ☑ | 2 | CompetitiveRegion_Bin | Transaction |
| ☑ | 3 | zRegion | Transaction |
| ☐ | 4 | CustomerSpend_Bin | Transaction |
| ☐ | 5 | Customer_Loyalty | Transaction |
| ☐ | 6 | OrderSize_Bin | Transaction |
| ☐ | 7 | Price_Change_Group | Transaction |
| ☐ | 8 | Region | Transaction |

Save Cancel

## Step 2- Set Model Parameters

**Regression Parameters**

| | |
|---|---|
| Enable Trace Debug | ☐ |
| Delta Days | 180 |
| Delta Lag Days | 180 |
| Max Price Delta (%) | 50 |
| Max Quantity Delta (%) | 50 |
| Transaction Threshold | 20 |
| MuA | 0.0000 |
| MuB | -1.0000 |
| SigA | 0.1000 |
| SigB | 0.2500 |
| SigEpsHB | 1.0000 |
| SigEpsLB | 0.0100 |
| Number of Samples | 10,000 |
| Burn-in (%) | 20 |
| Calculation Time Limit (hours) | 5.000 |
| Attribute for Partitioning | 1 \| Customer_Program |

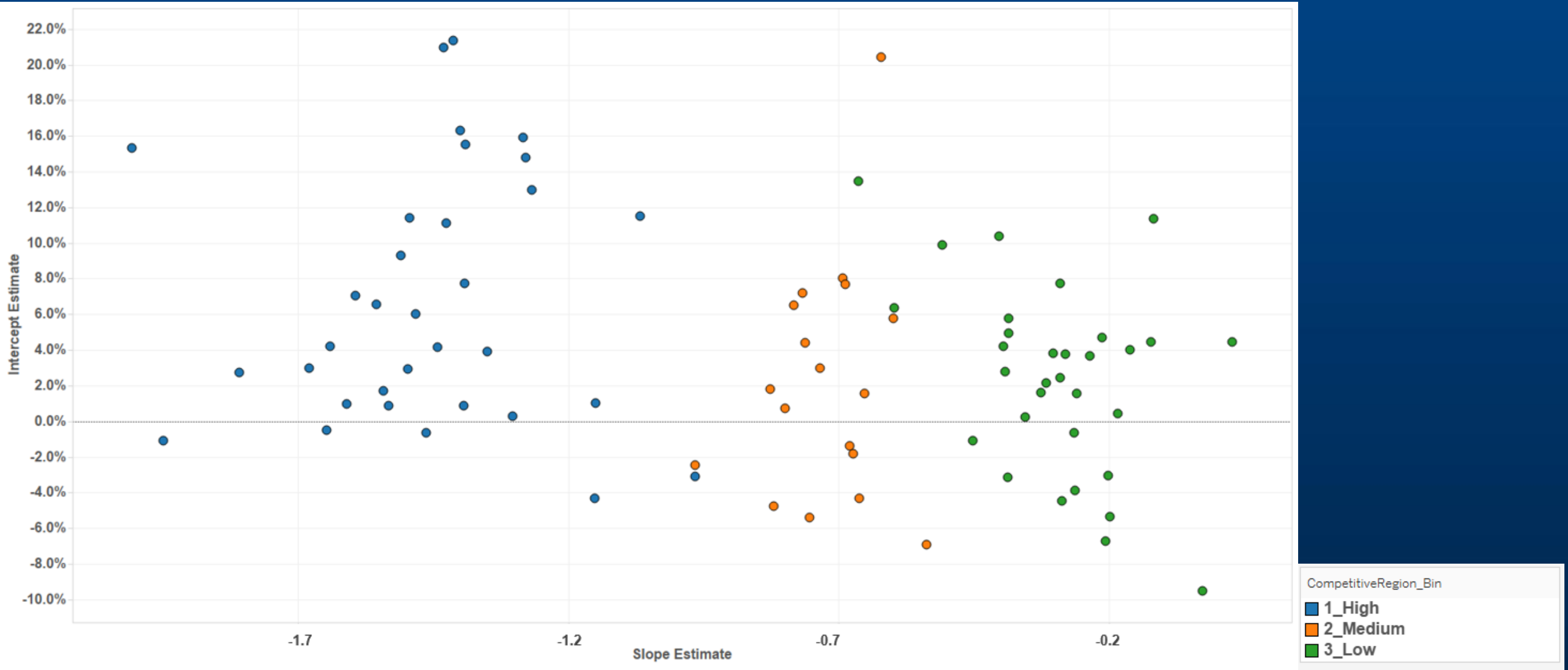
## Step 3- Run the job!

**Jobs**

- Compute regression

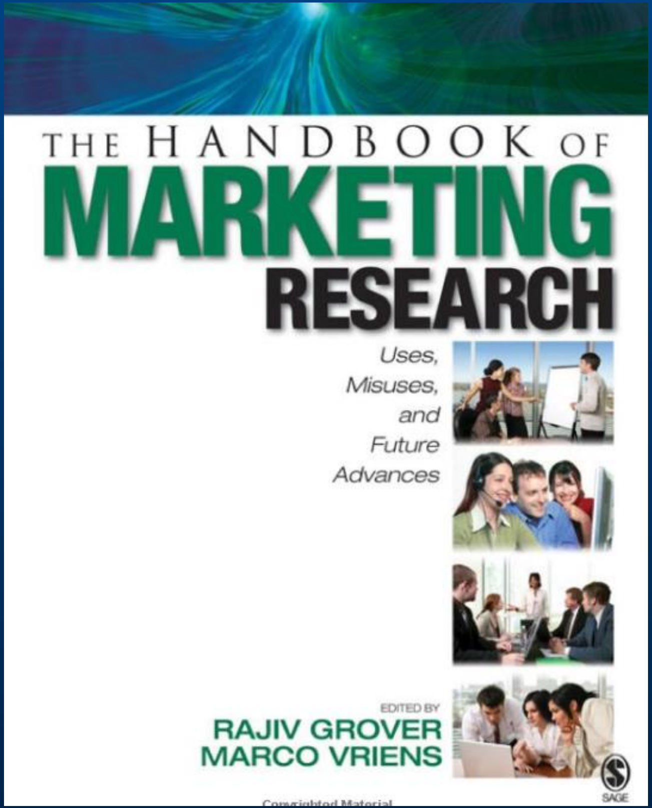
Run Job

# Output



22.0%
20.0%
18.0%
16.0%
14.0%
12.0%
10.0%
8.0%
6.0%
4.0%
2.0%
0.0%
-2.0%
-4.0%
-6.0%
-8.0%
-10.0%
Intercept Estimate
-1.7
-1.2
-0.7
-0.2
Slope Estimate
CompetitiveRegion_Bin
1_High
2_Medium
3_Low

# Learn more?

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## Hierarchical Bayes Models

Greg M. Allenby
*Ohio State University*

Peter E. Rossi
*University of Chicago*





include the relationship of needs to desired attributes or wants, wants to brand beliefs and consideration sets, and consideration sets to preference orderings and choice. These extended models are often conceptualized in a hierarchical manner, where movement from one model component to the next proceeds in a logical manner. Estimation of these new integrated models is not possible without Bayesian methods.

The nature and determinants of heterogeneity have also received much attention over the past 10 years. Across dozens of studies, the distribution of heterogeneity has been shown to be better represented by a continuous, not a discrete, distribution (e.g., from a finite mixture model) of heterogeneity (Allenby, Arora, & Ginter, 1998). This has important implications for analysis connected with market segmentation, where researchers often incorrectly assert the existence of a small number of homogeneous groups. Bayesian methods are being used to identify new basis variables that point to brand preferences (Yang, Allenby, & Fennell, 2002), new ways of dealing with respondent heterogeneity in scale usage (Rossi, Gilula, & Allenby, 2001), and new ways of characterizing social networks and their impact on demand (e.g., interdependent preferences; Yang & Allenby, 2003). These developments would again not be possible without modern Bayesian methods.

In this chapter, we provide an introduction to hierarchical Bayes models and an overview of successful applications. Underlying assumptions are discussed in the next section, followed by an introduction to the computational arm of

look behind the data requires models that reflect associations of interest. Consider, for example, an analysis designed to determine the influence of price on the demand for a product or service. If the offering is available in continuous units (e.g., minutes of cell phone usage), then a regression model (see Chapter 13) can be used to measure price sensitivity using the following model:

$$y_t = \beta_0 + \beta_1 \text{price}_t + \varepsilon_t \; ; \; \varepsilon_t \sim \text{Normal}(0, \sigma^2) \quad (1)$$

where $y_t$ denotes demand at time $t$, $\text{price}_t$ is the price at time $t$, and $\beta_0$, $\beta_1$, and $\sigma^2$ are parameters to be estimated from the data. The parameters $\beta_0$ and $\beta_1$ define the expected association between price and demand. Given the price at any time, $t$, one can compute $\beta_0 + \beta_1\text{price}_t$ and obtain the expected demand, $y_t$. The parameter $\sigma^2$ is the variance of the error term $\varepsilon_t$ and reflects the uncertainty associated with relationship. Large values of $\sigma^2$ are associated with noisy predictions, and small values of $\sigma^2$ indicate an association without much uncertainty.

Individual-level demand, however, is rarely characterized by such a smooth, continuous association. The most frequently observed quantity of demand at the individual level is 0, and the next most frequently observed quantity is 1. Marketing data, at the individual level, are inherently discrete and noncontinuous. One approach to dealing with the discreteness of marketing data is to assume that the observed demand is a censored realization of an underlying continuous model:

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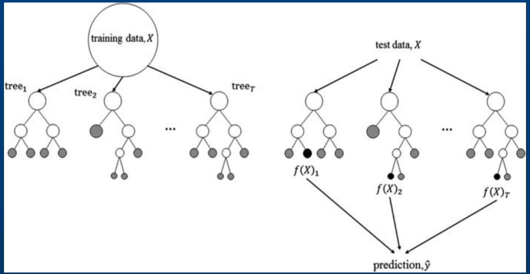
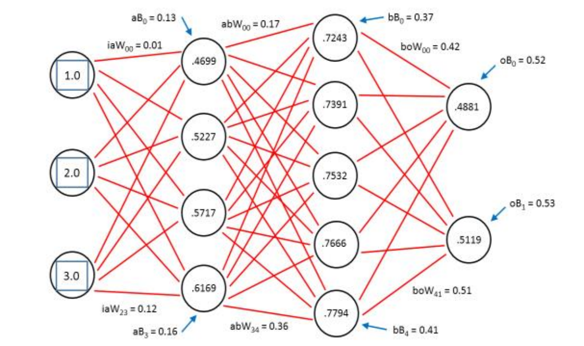
# The Zilliant IQ Platform Brings Best-In-Class AI to B2B

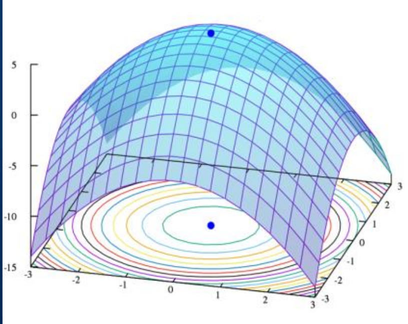
## Random Forest



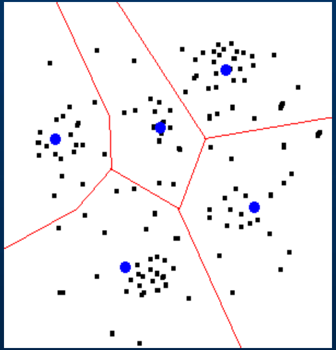

## Neural Network / Deep Learning




## Convex Optimization



## Clustering



## Association Rules

$$Rule:\ X \Rightarrow Y$$

$$Support = \frac{frq(X,Y)}{N}$$

$$Confidence = \frac{frq(X,Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

# Codes and Slides:

https://github.com/AmirMK/ODSC

# Question and/or Discussion:

Amir.Meimand@Zilliant.com

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