# OPEN DATA SCIENCE CONFERENCE

Boston | May 1 - 4 2018



@ODSC



# Bayesian Hieratical Model for Predictive Analytic

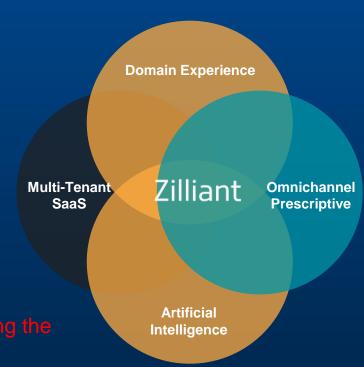
Amir Meimand
Director of R&D, Pricing Science, Zilliant



#### 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 Al-enriched SaaS platform for maximizing the lifetime value of B2B customer relationships.



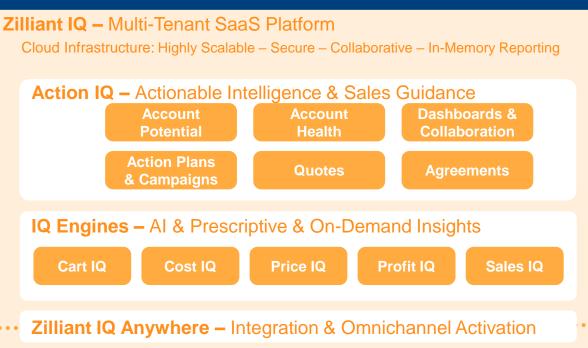


#### **About Zilliant**

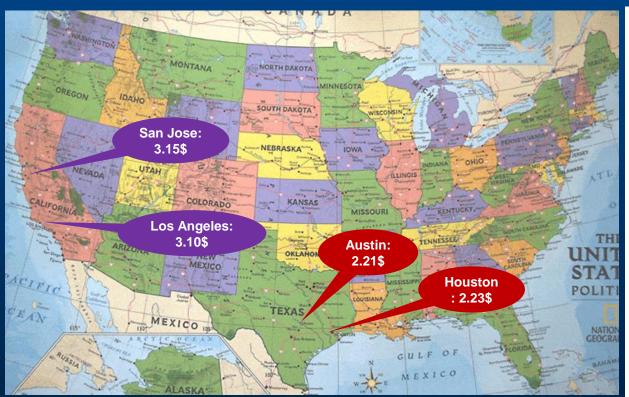
#### Zilliant IQ

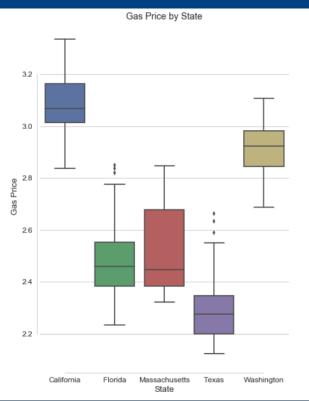
Converting Strategic Insights into Account Specific Action Plans

Ex. Data In **Product** Master Customer Master **Transaction** Data Win / Loss Data 3<sup>rd</sup> Party Data Competitor **Price Data** 

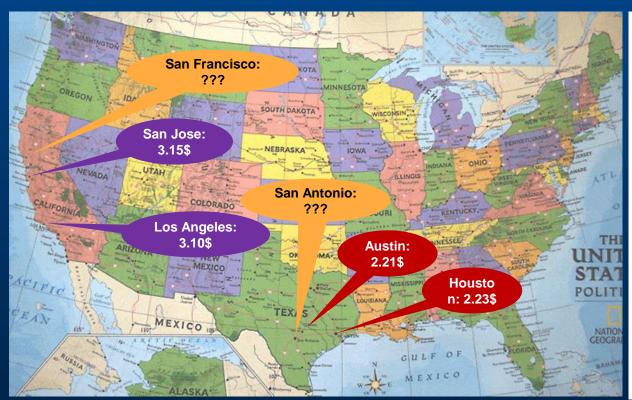


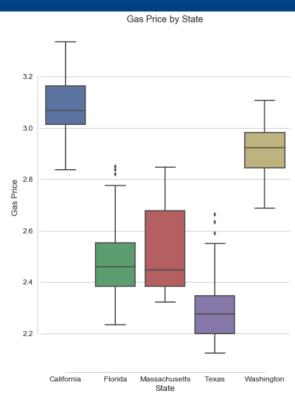






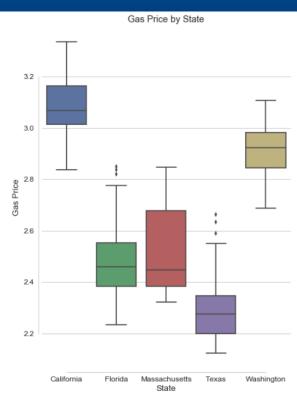




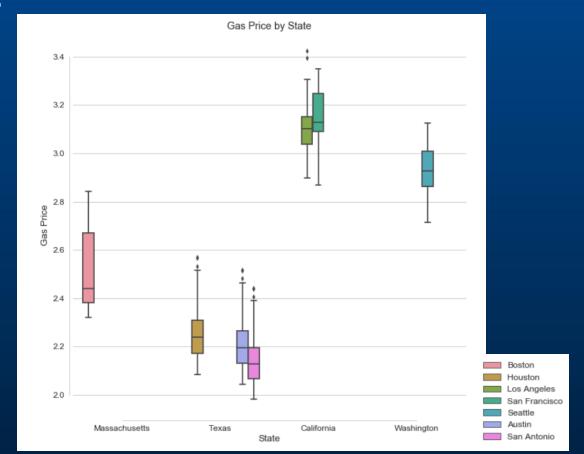














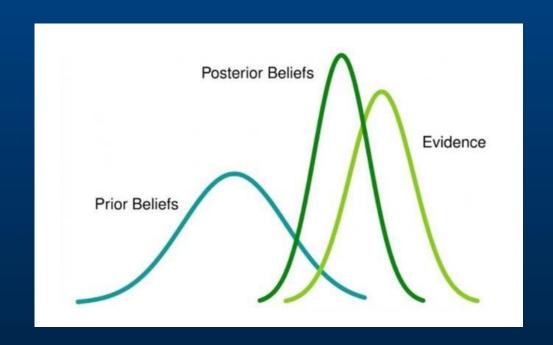


#### San Antonio:

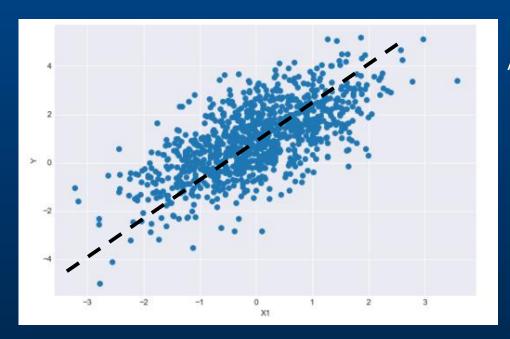
- Station 1: 3.5\$
- Station 2: 3.8\$



# Bayesian Models

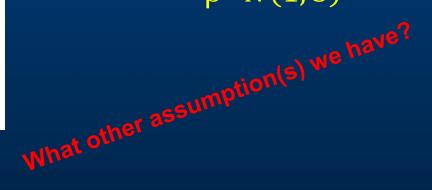






Assumed relationship:  $y = \alpha + \beta x$ 

Priors:  $\alpha \sim N(0, 10)$   $\beta \sim N(1, 5)$ 





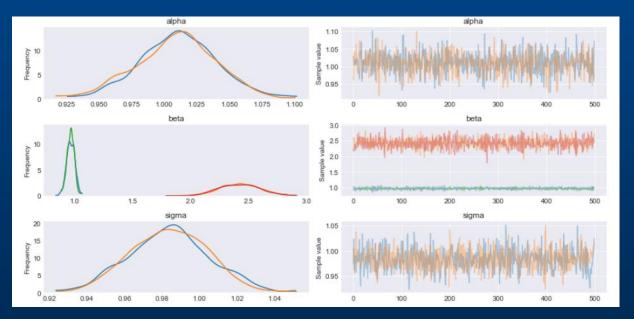
- 1- What is the target variable? Y which depends on Alpha and Beta
- 2- What is assumed (potential distribution)? Normal Distribution
- 3- Define priors

Alpha and/or Beta distribution



```
regression model = pm.Model()
with regression model:
    alpha = pm.Normal('alpha', mu=0, sd=10)
                                            Create stochastic variables
    beta = pm.Normal('beta', mu=1, sd=5)
    sigma = pm.HalfNormal('sigma', sd=1)
                                        Create deterministic variable
   mu = alpha + beta*X1
   Y obs = pm.Normal('Y obs', mu=mu, sd=sigma, observed=Y)
```



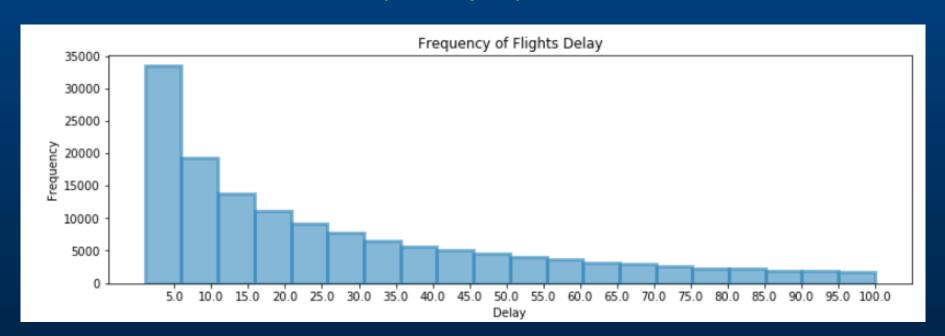


	mean	sd	mc_error	hpd_2.5	hpd_97.5	n_eff	Rhat
alpha	1.009507	0.029933	0.000790	0.950972	1.065191	1515.745188	1.000558
beta0	0.967910	0.032986	0.000856	0.905172	1.032044	1451.511508	0.999007
beta1	2.420182	0.164576	0.004431	2.120133	2.747157	1641.803594	0.999708
sigma	0.983615	0.021083	0.000603	0.945488	1.024915	1201.344314	0.999019





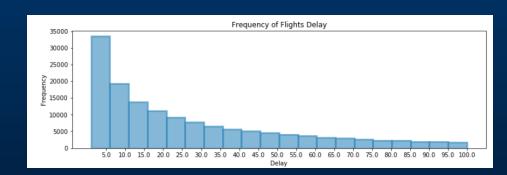
#### **Evidence (IAH Airport)**



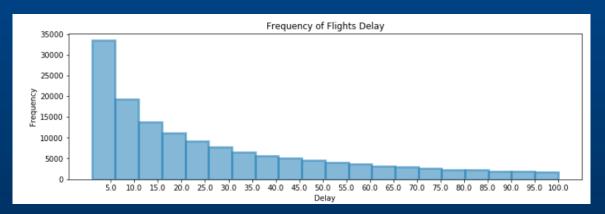


### Modeling Step

- 1- What is the target variable?
- 2- What is assumed (potential distribution)?
- 3- Define priors

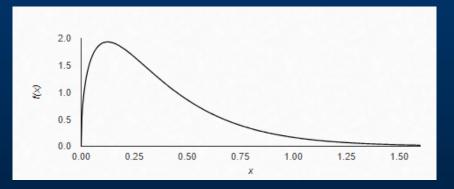






#### **Evidence (IAH Airport)**

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



**Prior Belief** 



```
Flight_Delay = pm.Model()
with Flight_Delay:
    # Prior Distribution

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

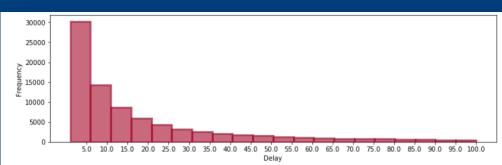
# Likelihood (sampling distribution) of observations
Y_obs = pm.Exponential('Y_obs', rate, observed=x)
```

Prior Distribution of target variable

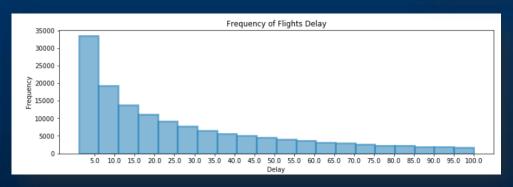
Relationship between



#### **Evidence (ORD Airport)**

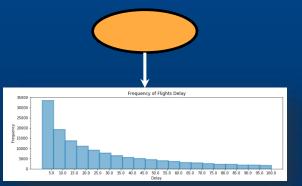


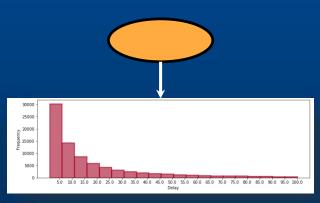
#### **Evidence (IAH Airport)**

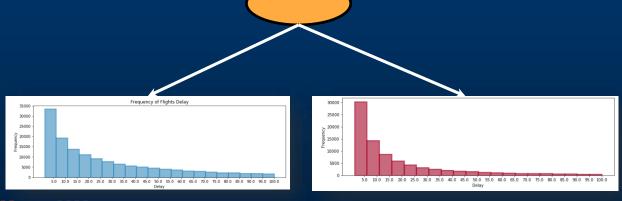


### ıllı zilliant

**Every one has its own model!** 



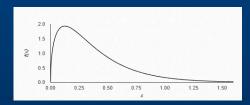




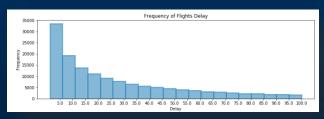
All have one model!

### ıllı zilliant

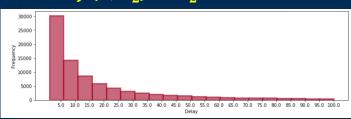
#### $Gamma(\alpha_1, \beta_1)$



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



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



```
Flight_Delay = 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)
```



### 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** 

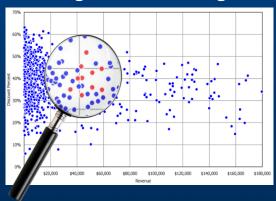
...could evaluate every customer relationship, every day and recommend action?

How would that impact customer lifespan, revenue and profit?

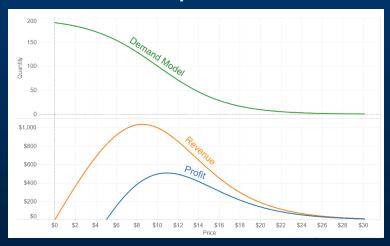
#### **Price Optimization**

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

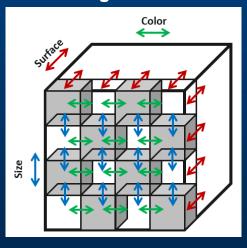
#### **Segment Clustering**



#### **Convex Optimization**

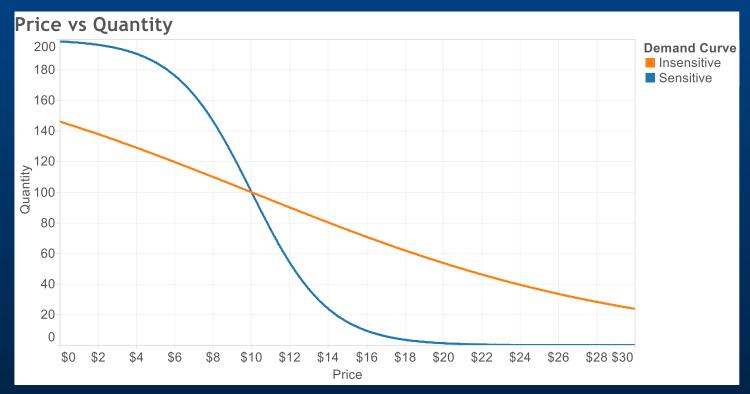


#### **Pricing Constraints**





# **Price Elasticity**



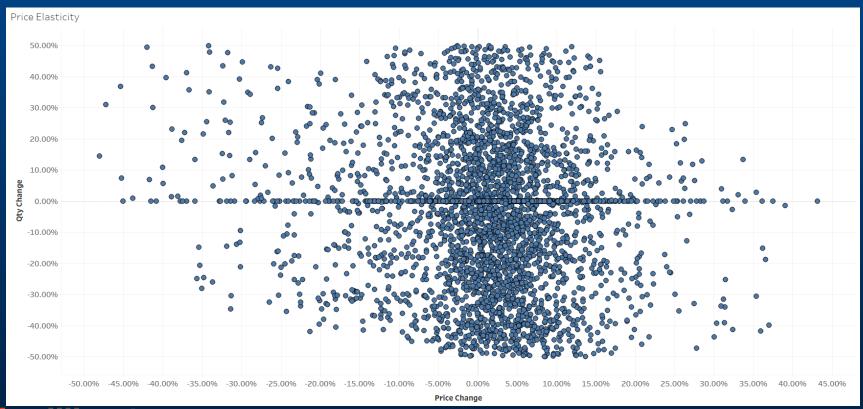


# What we hope (like) to see



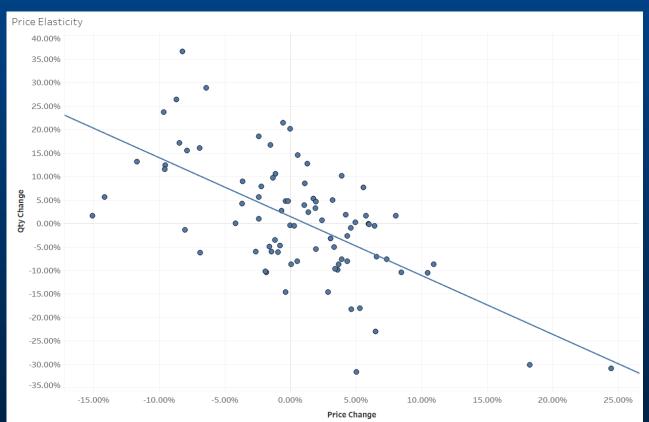


### What we really see!





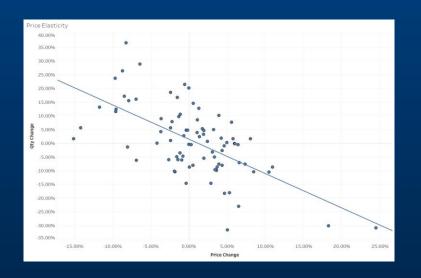
### Fix it!



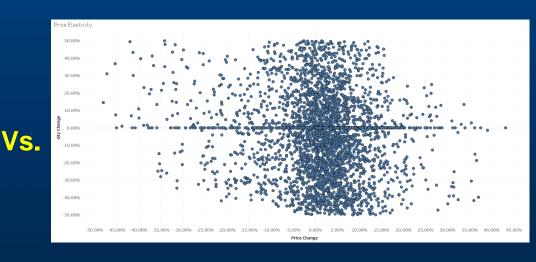


# Why Hieratical Model?

#### **Clean Data, Less Data Points**

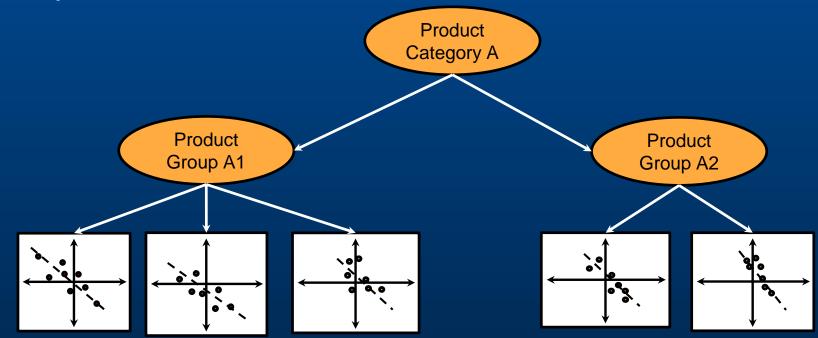


#### **Noisy Data, Many Data Points**





# Why Hieratical Model?





### Bayesian Hieratical Model

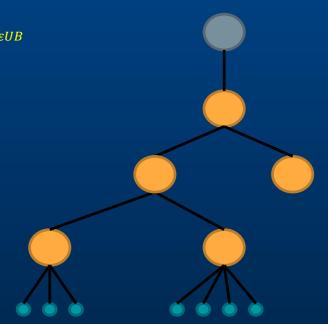
Hyperpriors:  $\mu_{\alpha}$ ,  $\mu_{\beta}$ ,  $\sigma_{\alpha}$ ,  $\sigma_{\beta}$ ,  $\sigma_{\varepsilon LB}$ ,  $\sigma_{\varepsilon UB}$ 

Level 0:  $\mu_{\alpha,0}$ ,  $\mu_{\beta,0}$ 

Level 1:  $\mu_{\alpha,1}$ ,  $\mu_{\beta,1}$ 

Level 2:  $\alpha_i$ ,  $\beta_i$ 

Data:  $\Delta Q_i$ ,  $\Delta P_i$ 



$$\mu_{\alpha,k} \sim Normal(\mu_{\alpha,k-1}, \sigma_{\alpha})$$
  
 $\mu_{\beta,k} \sim Normal(\mu_{\beta,k-1}, \sigma_{\beta})$ 

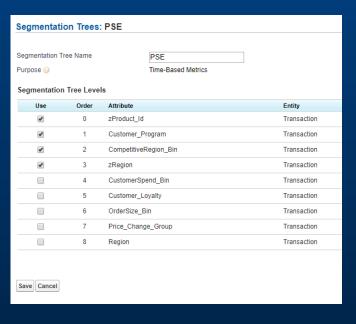
$$\Delta Q_i = \alpha_i + \beta_i \cdot \Delta P_i + \varepsilon_i$$

 $\alpha_{j} \sim Normal(\mu_{\alpha,2}, \sigma_{\alpha})$   $\beta_{j} \sim Normal(\mu_{\beta,2}, \sigma_{\beta})$   $\varepsilon_{i} \sim Normal(0, \sigma_{\varepsilon})$   $\sigma_{\varepsilon} \sim Uniform(\sigma_{\varepsilon LB}, \sigma_{\varepsilon UB})$ 

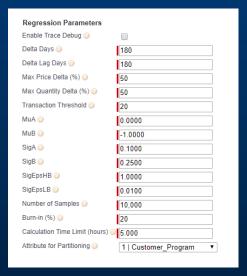


### Zilliant ML Platform (Point and Click!)

#### **Step 1- Define Hieratical Levels**



#### **Step 2- Set Model Parameters**

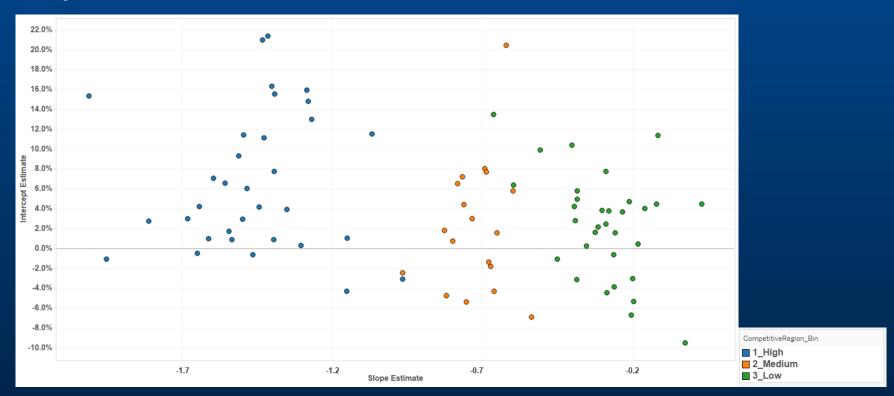


#### Step 3- Run the job!





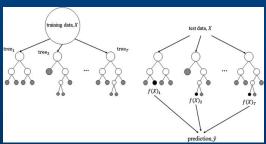
# Output



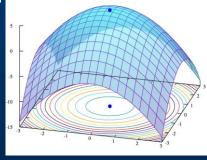


#### The Zilliant IQ Platform Brings Best-In-Class AI to B2B

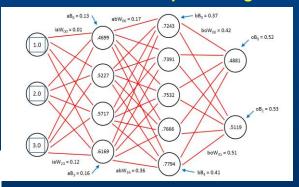
#### **Random Forest**



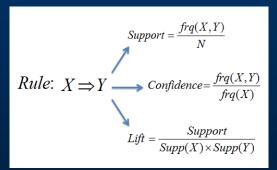
#### **Convex Optimization**



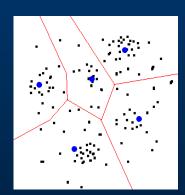
#### **Neural Network / Deep Learning**



#### **Association Rules**



#### Clustering





#### **Codes and Slides:**

https://github.com/AmirMK/ODSC

#### **Question and/or Discussion:**

Amir.Meimand@Zilliant.com

