

# Meal Price Optimization

½ Consulting, Inc.

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Group 1:

Qiuxia Chen (Katalia)

Xuechen He (Celia)

Mei Lu (May)

Junkai Zhong (Caesar)



# Structure

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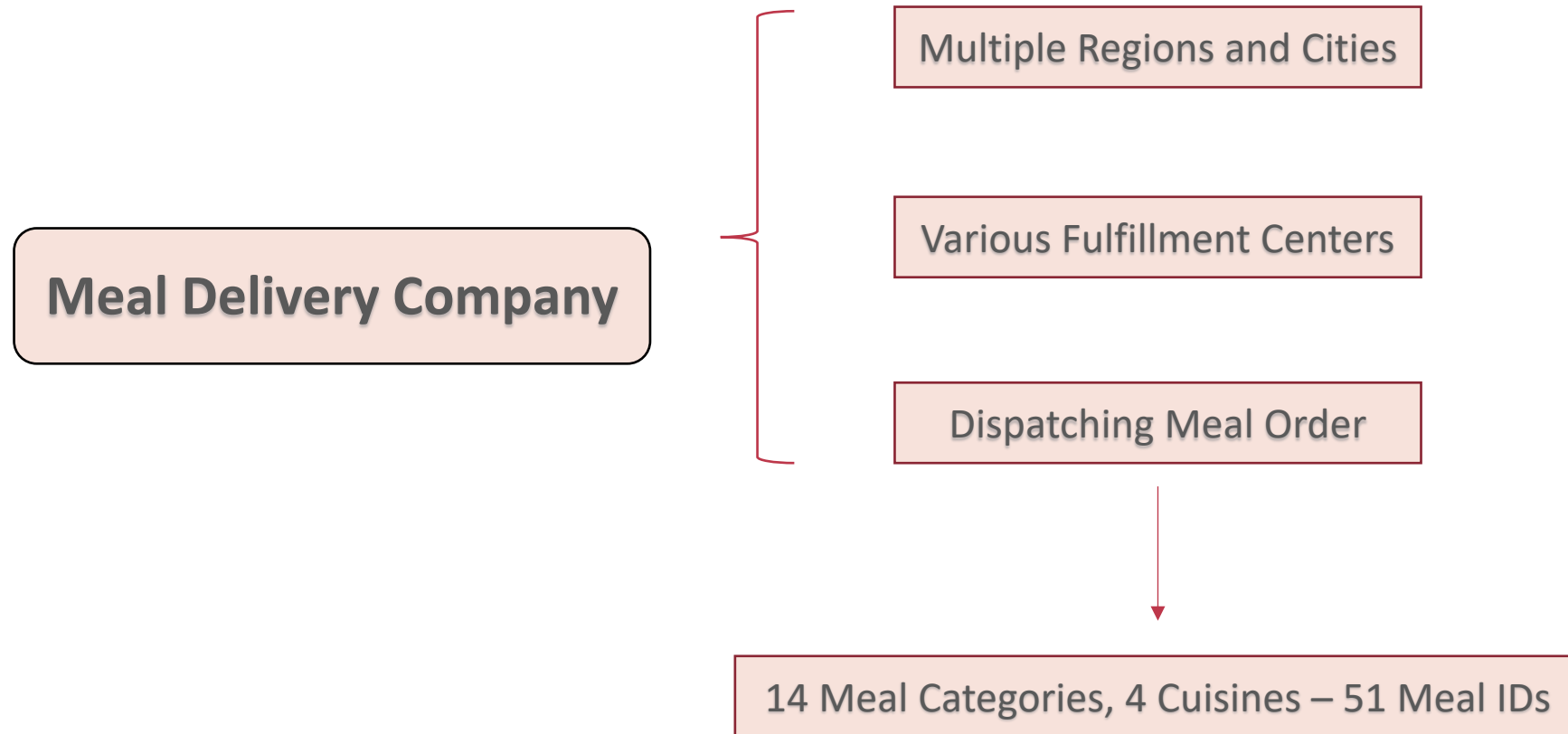
Background

Data Analysis

Modeling

Conclusion

# Background



# Industry Overview

## Physical Footprint



**15,000**

Distribution centers

*Texas, California, and Florida are leading states*



**288 million**

Square feet of distribution space

*Equivalent to 5,000 football fields*



**8.7 billion**

Cases delivered

*Nearly 24 million cases per day*



**3.2 billion**

Vehicle miles per year

*Around the Earth 330,000 times, or 1,700 roundtrips to the sun*



**820 million**

Gallons of fuel per year

*More than 1,240 Olympic-size swimming pools*



**131,000**

Drivers

*3.75 percent of all truck drivers in the U.S.*

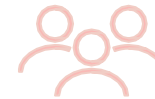
## Economic Footprint



**\$280 billion**

Industry annual sales

*Approximately the GDP of Louisiana*



**350,000**

Employed by industry

*5.25 percent of all wholesale jobs*



Employee Spending



**700,000**

Ancillary jobs

*Industry + ancillary jobs = population of Delaware*



**\$51 billion**

U.S. GDP

*0.25 percent of the total U.S. economy*



**\$14 billion**

Federal, state, and local tax revenues

*\$7.2 billion in federal taxes, and \$6.9 billion in state and local taxes*

# Data Overview

Variable	Definition
id	Unique ID
week	Week No
center_id	Unique ID for fulfillment center
meal_id	Unique ID for the meal
checkout_price	Final price including discount, taxes & delivery charges
base_price	Base price of the meal
emailer_for_promotion	Email sent for promotion of meal
homepage_featured	Meal featured at homepage
num_orders	(Target) Orders Count

Variable	Definition
center_id	Unique ID for fulfillment center
city_code	Unique code for city
region_code	Unique code for region
center_type	Anonymized center type
op_area	Area of operation (in km^2)

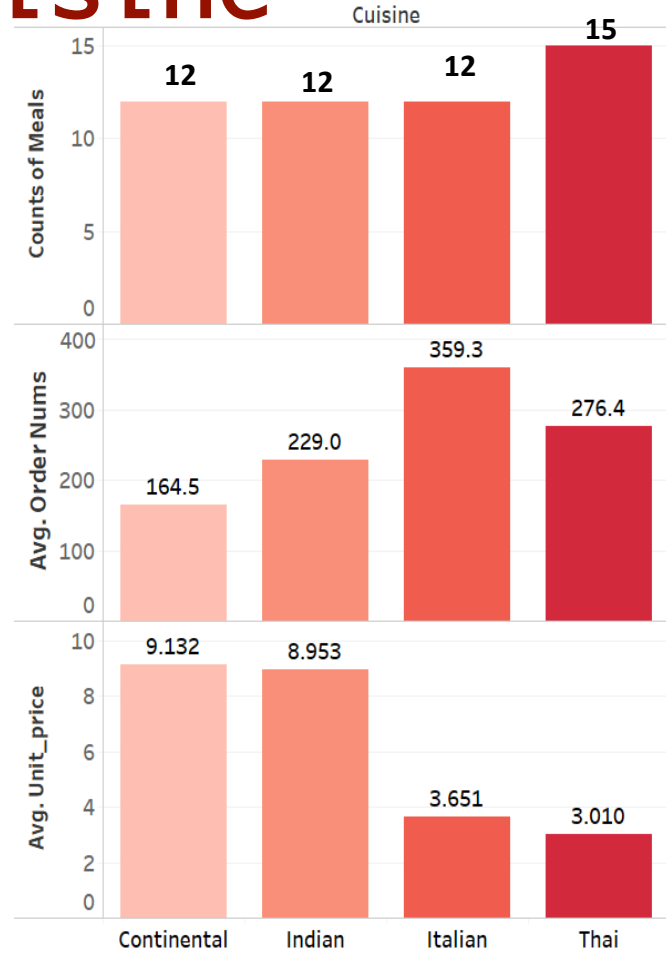
Variable	Definition
meal_id	Unique ID for the meal
category	Type of meal (beverages/snacks/soups...)
cuisine	Meal cuisine (Indian/Italian/...)

# Exploratory Data Analysis: by Category



- 14 categories, 51 meal products
- Most popular meal: Rice Bowl, Sandwich and Salad
- Most expensive meal: Biryani, Seafood and Fish
- The order numbers seem to be negatively correlated with the unit price

# Exploratory Data Analysis: by Cuisine



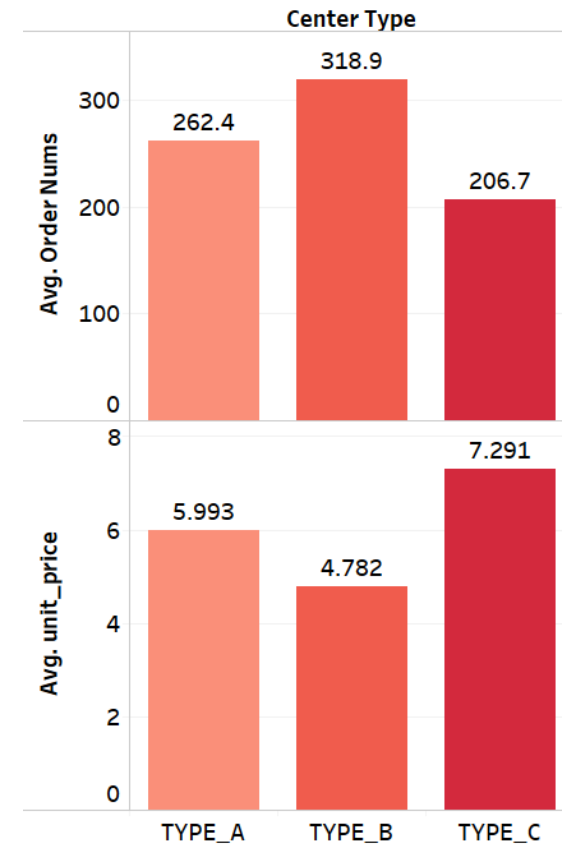
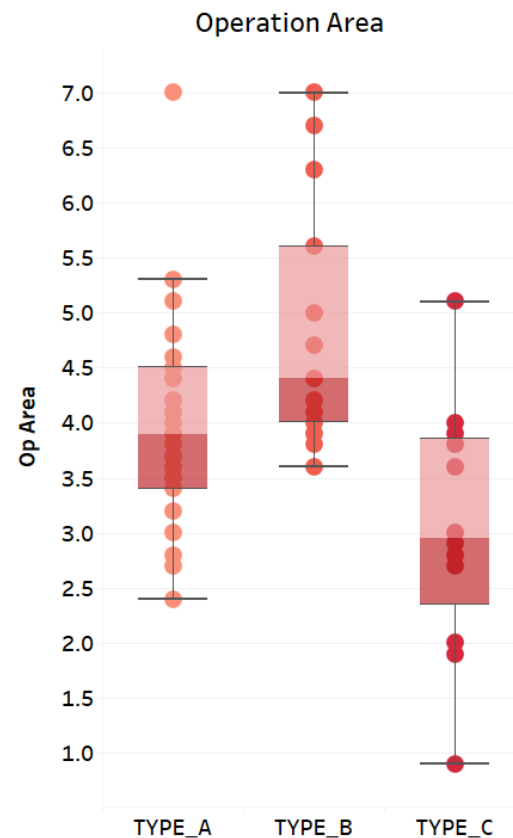
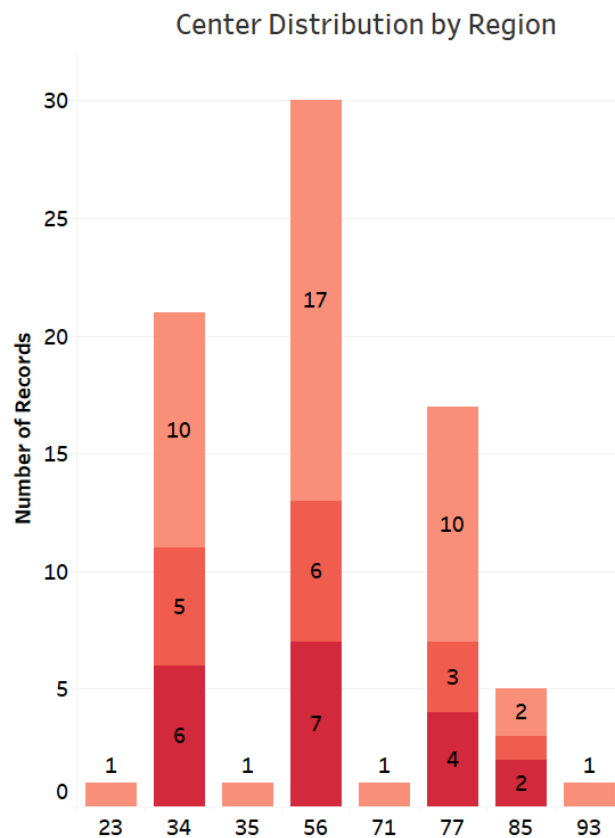
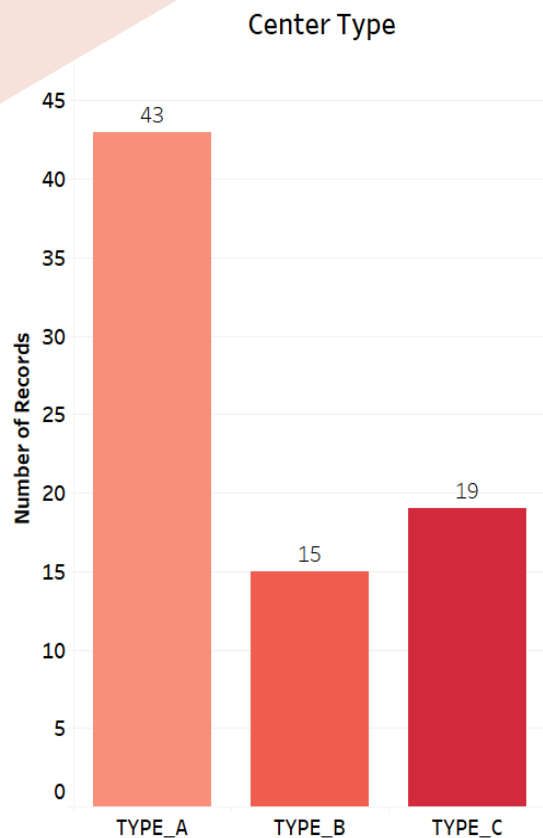
- 4 cuisines
- Order numbers: Italian > Thai > Indian > Continental
- Unit price: Continental > Indian > Italian > Thai

Category- Cuisine combination

Category	Cuisine			
	Continental	Indian	Italian	Thai
Beverages	3	3	3	3
Biryani		3		
Desert		3		
Extras				3
Fish	3			
Other Snacks				3
Pasta			3	
Pizza	3			
Rice Bowl		3		
Salad			3	
Sandwich			3	
Seafood	3			
Soup				3
Starters				3

- Beverage 4 favors, other categories belong to one specific cuisine
- Each cuisine contain 4~5 different kinds of meals

# Exploratory Data Analysis: by Center



- 3 types, 77 centers
- number: type A > type C > type B

- 8 regions
- Type A center in every region

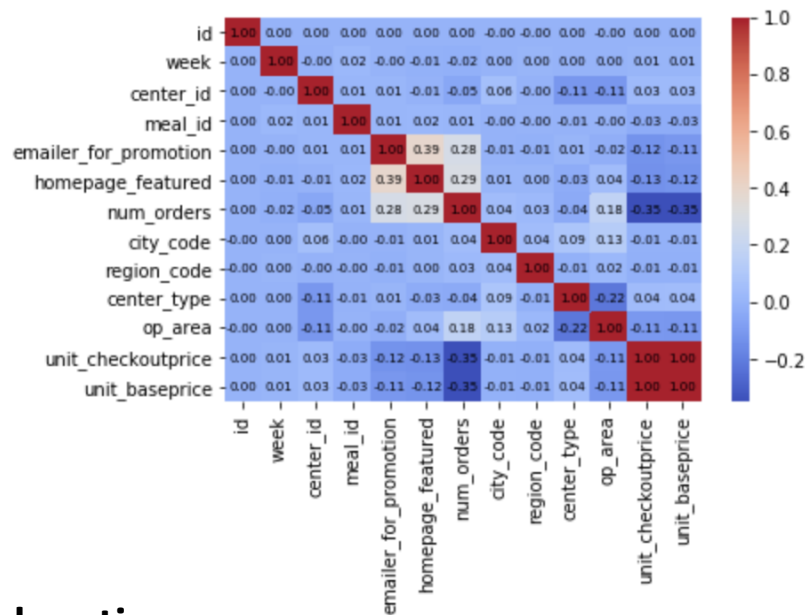
- Average area: B > A > C

- Order number: B > A > C
- Unit price: C > A > B

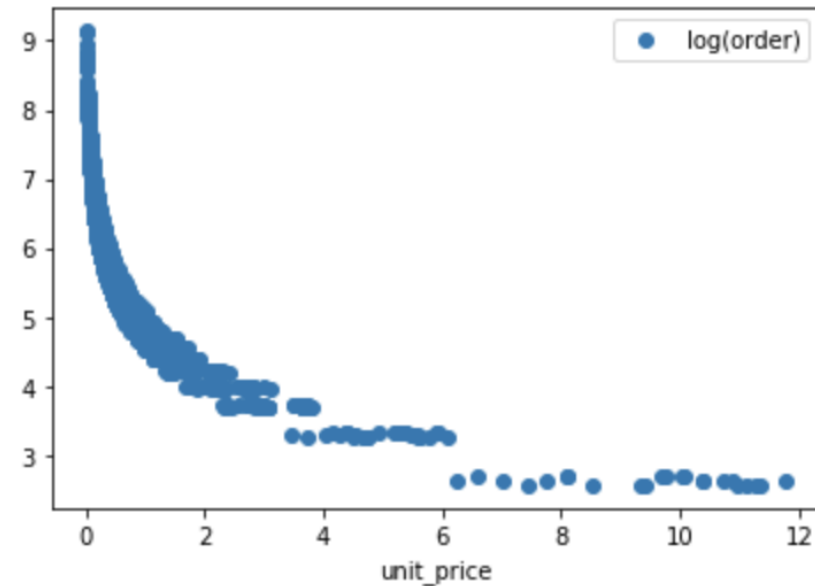


# How to build Demand Model

Correlation Matrix



log linear model



## Data explanation:

It is shown that the number of orders is highly correlated with unit price, emailer promotion, homepage featured, and op\_a rea.

The relationship between unit checkout price and number of orders, we will run a log linear model

# Demand Model

- center\_type A, B, C as dummy variables **type\_A, type\_B and type\_C**
- Emailer\_for\_promotion, homepage\_featured are binary variables
- Log(num\_orders) is dependent variable

$$\text{Log}(D) = \beta_0 + \beta_1 \text{unit\_checkout\_price} + \beta_2 \text{promotion} + \beta_3 \text{featured} + \beta_4 \text{area} + \beta_5 \text{type\_A} + \beta_6 \text{type\_B} + \beta_7 \text{type\_C}$$

	coef	std err	t	P> t	[0.025	0.975]
const	3.6674	0.004	974.947	0.000	3.660	3.675
unit_checkoutprice	-0.0965	0.000	-778.615	0.000	-0.097	-0.096
emailer_for_promotion	0.4284	0.004	96.660	0.000	0.420	0.437
homepage_featured	0.4370	0.004	112.536	0.000	0.429	0.445
op_area	0.1183	0.001	102.187	0.000	0.116	0.121
center_type_TYPE_A	1.2224	0.002	652.833	0.000	1.219	1.226
center_type_TYPE_B	1.2610	0.003	441.239	0.000	1.255	1.267
center_type_TYPE_C	1.1840	0.002	600.397	0.000	1.180	1.188

# Model for Cuisines

Cuisines	Model	Price Coff.	R-square
Thai	$\text{Log}(D) = 3.8 - 0.19 \cdot \text{unitprice} + 0.16 \cdot \text{promotion} + 0.61 \cdot \text{featured} + 0.11 \cdot \text{area} + 1.26 \cdot \text{type\_A} + 1.42 \cdot \text{type\_B} + 1.11 \cdot \text{type\_C}$	-0.1857	0.694
Italian	$\text{Log}(D) = 3.8 - 0.13 \cdot \text{unitprice} + 0.42 \cdot \text{promotion} + 0.41 \cdot \text{featured} + 0.17 \cdot \text{area} + 1.25 \cdot \text{type\_A} + 1.19 \cdot \text{type\_B} + 1.35 \cdot \text{type\_C}$	-0.1327	0.667
Indian	$\text{Log}(D) = 3.66 - 0.1 \cdot \text{unitprice} + 0.85 \cdot \text{promotion} + 0.19 \cdot \text{featured} + 0.09 \cdot \text{area} + 1.2 \cdot \text{type\_A} + 1.25 \cdot \text{type\_B} + 1.21 \cdot \text{type\_C}$	-0.0952	0.642
Continental	$\text{Log}(D) = 3.56 - 0.06 \cdot \text{unitprice} + 0.39 \cdot \text{promotion} + 0.49 \cdot \text{featured} + 0.08 \cdot \text{area} + 1.19 \cdot \text{type\_A} + 1.09 \cdot \text{type\_B} + 1.28 \cdot \text{type\_C}$	-0.0641	0.768

## Data explanation:

The coefficient on unit price for Continental, Indian, Italian, Thai food are  $0.06 < 0.1 < 0.13 < 0.19$  respectively, we can conclude that the Thai food is more price sensitivity than others.

# Price Sensitivity for Categories

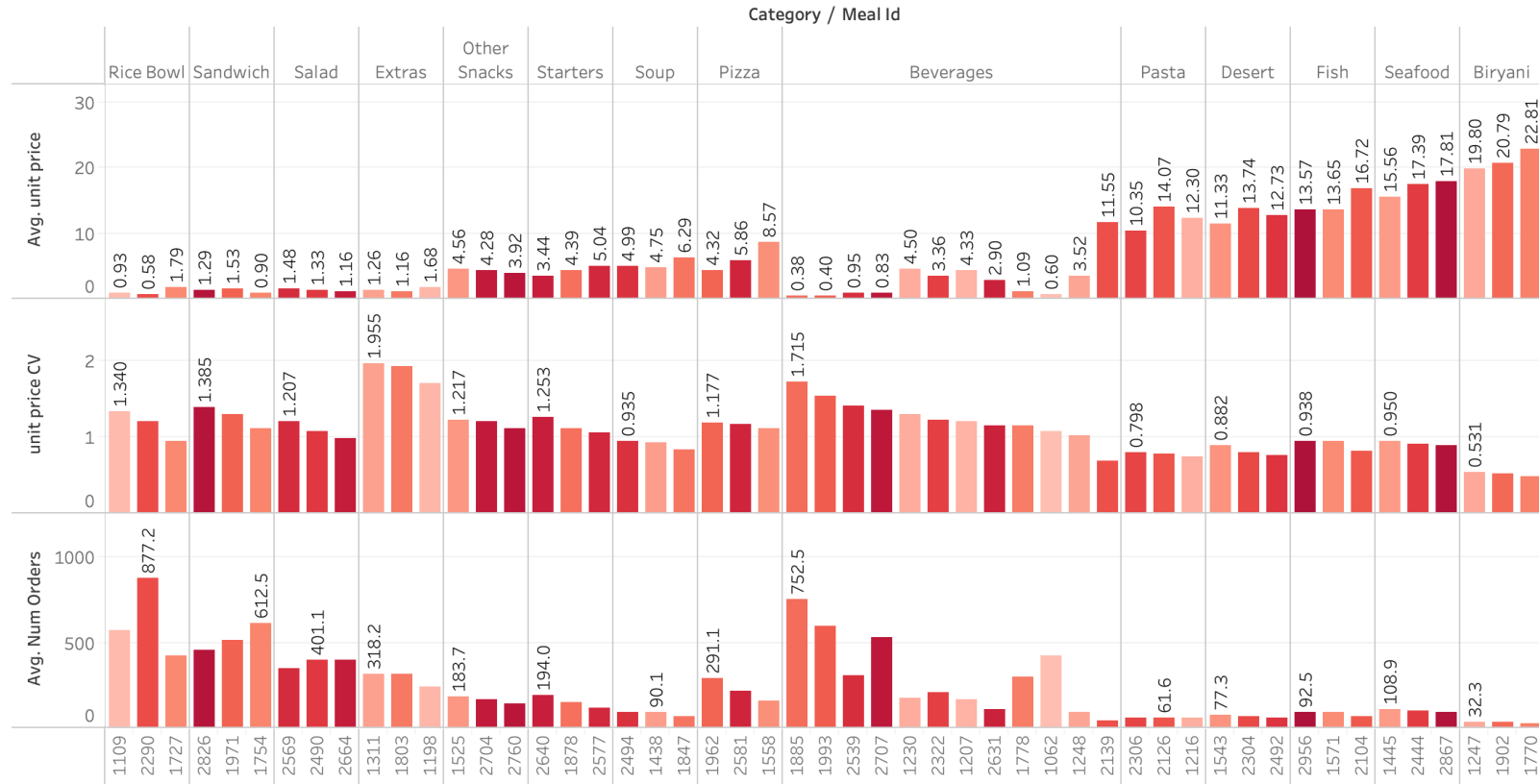
## Coefficient of Unit Checkout Price

Beverage -0.17	<b>Desert</b> -0.67	Fish -0.06	Pasta -0.07	Rice Bowl -0.34	Sandwich -0.3	Soup -0.15
Biryani -0.05	Extras -0.19	Other Snacks -0.14	Pizza -0.08	Salad -0.32	<b>Seafood</b> -0.04	Starters -0.14

### Data explanation:

- Desert has the largest price sensitivity, price increase by \$1, the demand decrease by 67%
- Seafood has the smallest price sensitivity, demand change by 4% with the price goes up \$1.

# Item Selection



Average of unit price, unit price CV and average of Num Orders for each Meal Id broken down by Category. Color shows details about Meal Id. The view is filtered on Category, which keeps 14 of 14 members.

We choose three items with the highest price coefficient of variation in different unit level and categories  
 Beverage : Meal id 1885 (\$0.17), Starters: Meal id 2640(\$3.44), Desert: Meal id 1543(\$11.33)

# Item Based Model

## Beverage - 1885

	coef	std err	t	P> t	[0.025	0.975]
<b>const</b>	3.9922	0.018	219.539	0.000	3.957	4.028
<b>unit_checkoutprice</b>	-0.6497	0.009	-73.492	0.000	-0.667	-0.632
<b>emailer_for_promotion</b>	0.1757	0.027	6.487	0.000	0.123	0.229
<b>homepage_featured</b>	0.3940	0.012	34.056	0.000	0.371	0.417
<b>op_area</b>	0.2628	0.006	47.546	0.000	0.252	0.274
<b>center_type_TYPE_A</b>	1.4580	0.009	170.611	0.000	1.441	1.475
<b>center_type_TYPE_B</b>	1.4135	0.013	107.596	0.000	1.388	1.439
<b>center_type_TYPE_C</b>	1.1206	0.009	118.112	0.000	1.102	1.139

R-square: 0.662

## Starters - 2640

	coef	std err	t	P> t	[0.025	0.975]
<b>const</b>	3.6843	0.014	260.614	0.000	3.657	3.712
<b>unit_checkoutprice</b>	-0.1411	0.001	-126.930	0.000	-0.143	-0.139
<b>emailer_for_promotion</b>	0.5626	0.021	27.413	0.000	0.522	0.603
<b>homepage_featured</b>	0.2094	0.015	13.971	0.000	0.180	0.239
<b>op_area</b>	0.1086	0.004	25.996	0.000	0.100	0.117
<b>center_type_TYPE_A</b>	1.2088	0.006	189.022	0.000	1.196	1.221
<b>center_type_TYPE_B</b>	1.6047	0.010	162.661	0.000	1.585	1.624
<b>center_type_TYPE_C</b>	0.8709	0.009	98.682	0.000	0.854	0.888

R-square:0.822

## Desert - 1543

	coef	std err	t	P> t	[0.025	0.975]
<b>const</b>	3.4151	0.012	295.277	0.000	3.392	3.438
<b>unit_checkoutprice</b>	-0.0681	0.000	-205.273	0.000	-0.069	-0.067
<b>emailer_for_promotion</b>	0.2524	0.013	19.491	0.000	0.227	0.278
<b>homepage_featured</b>	0.0524	0.009	5.571	0.000	0.034	0.071
<b>op_area</b>	0.0647	0.003	19.138	0.000	0.058	0.071
<b>center_type_TYPE_A</b>	1.0713	0.006	192.223	0.000	1.060	1.082
<b>center_type_TYPE_B</b>	1.2456	0.008	151.650	0.000	1.230	1.262
<b>center_type_TYPE_C</b>	1.0981	0.006	194.089	0.000	1.087	1.109

R-square: 0.842

# Revenue Optimization

Assuming that we apply model

- 1) With only Center Type A, which has an average operation area of 4.08
- 2) No promotion notice
- 3) No homepage feature

**The number of orders would be**

**Beverage-1885:  $\text{Log}(D) = 3.99 - 0.65 \cdot \text{unit\_price} + 0.26 \cdot 4.08 + 1.46 \cdot 1$**

**Soup-1438:  $\text{Log}(D) = 3.50 - 0.16 \cdot \text{unit\_price} + 0.06 \cdot 4.08 + 1.17 \cdot 1$**

**Desert-1543:  $\text{Log}(D) = 3.42 - 0.07 \cdot \text{unit\_price} + 0.06 \cdot 4.08 + 1.07 \cdot 1$**

Meal id	Optimal Price	demand	Optimal Revenue	Current revenue	Percentage of change
1885	1.54	247.35	380.54	204.83	+85.78%
1438	7.09	75.75	536.83	412.96	+29.99%
1543	14.68	42.56	624.83	778.64	-19.75%

# Model Evaluation

## Beverage – 1885 Interaction Effect

Dep. Variable:		log(order)	R-squared:		0.667		Dep. Variable:		log(order)	R-squared:		0.667		
Model:		OLS	Adj. R-squared:		0.667		Model:		OLS	Adj. R-squared:		0.667		
Method:		Least Squares	F-statistic:		3125.000		Method:		Least Squares	F-statistic:		3170.000		
Date:		Wed, 29 Apr 2020	Prob (F-statistic):		0.000		Date:		Wed, 29 Apr 2020	Prob (F-statistic):		0.000		
Time:		22:59:37	Log-Likelihood:		-8554.121		Time:		23:03:03	Log-Likelihood:		-8501.200		
No. Observations:		11092	AIC:		1.713e+04		No. Observations:		11092	AIC:		1.702e+04		
Df Residuals:		11084	BIC:		1.718e+04		Df Residuals:		11084	BIC:		1.708e+04		
Df Model:		7					Df Model:		7					
Covariance Type:		nonrobust					Covariance Type:		nonrobust					
		coef	std err	t	P> t	[0.025			coef	std err	t	P> t	[0.025	0.975]
const		3.9942	0.018	220.089	0.000	3.959	const		4.0029	0.018	221.410	0.000	3.967	4.038
unit_checkoutprice		-0.6473	0.009	-73.312	0.000	-0.665	unit_checkoutprice		-0.6308	0.009	-70.791	0.000	-0.648	-0.613
emailer_for_promotion		0.3097	0.033	9.327	0.000	0.245	emailer_for_promotion		0.1629	0.027	6.053	0.000	0.110	0.216
homepage_featured		0.3912	0.012	33.865	0.000	0.369	homepage_featured		0.4837	0.014	35.693	0.000	0.457	0.510
op_area		0.2621	0.006	47.519	0.000	0.251	op_area		0.2571	0.006	46.675	0.000	0.246	0.268
center_type_TYPE_A		1.4577	0.009	170.946	0.000	1.441	center_type_TYPE_A		1.4612	0.008	172.098	0.000	1.445	1.478
center_type_TYPE_B		1.4134	0.013	107.813	0.000	1.388	center_type_TYPE_B		1.4196	0.013	108.732	0.000	1.394	1.445
center_type_TYPE_C		1.1230	0.009	118.538	0.000	1.104	center_type_TYPE_C		1.1222	0.009	119.086	0.000	1.104	1.141
price_pro		-0.7324	0.105	-6.945	0.000	-0.939	price_feat		-0.4453	0.036	-12.483	0.000	-0.515	-0.375

$$\text{Price\_pro} = \text{unit\_price} * \text{Emailer\_for\_promotion}$$

```
Price_feat = unit_price * homepage_featured
```

Model	NO interaction	Add unit_price * emailer_for_promotion	Add unit_price * homepage_featured
Significant at 1% level	/	yes	yes
Adj.R^2	0.662	0.663	0.667
MSE	0.2740	0.2726	0.269



# Business Insights

- ❖ Item specific cost-efficient business investments
  - Emailer promotion
  - Homepage feature
  - Center type
- ❖ Future implication due to Covid-19
- ❖ Possible partnership with other operators from the industry

# Limitation

- ❖ Revenue optimization for the most part
- ❖ Unit Checkout Price vs. Unit Base Price
- ❖ Center Information, Possible Multicollinearity
- ❖ Omitted Variable Bias



**Thank You For Your Attention**