

# INFO 6105

## Data Science Engineering Methods and Tools

### Lecture 3

#### Sales of Child Car Seats

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**Key question** How to estimate accurately the distribution of demand?

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## Inventory Planning

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- The optimal order quantity depends on the distribution of demand

**Key question** How to estimate accurately the distribution of demand?

In reality, demand for a product is influenced by various factors, such as

- price
- product quality
- price of related products
- time of the year
- consumer's income,
- growth of population
- climatic conditions
- ...

To predict demand, we analyze the historical data to understand the relationship between sales and factors that influence sales.

# Sales of Child Car Seats

Consider a data set containing sales of child car seats at 400 different stores:

- **Sales** Unit sales (in thousands) at each location
- **Price** Price company charges for car seats at each site
- **CompPrice** Price charged by competitor at each location
- **Income** Community income level (in thousands of dollars)
- **Advertising** Local advertising budget for company at each location (in thousands of dollars)
- **Population** Population size in region (in thousands)
- **ShelveLoc** A factor with levels Bad, Medium, Good indicating the quality of the shelving location for the car seats at each site
- **Age** Average age of the local population
- **Education** Education level at each location
- **Urban** A factor with levels No and Yes to indicate whether the store is in an urban or rural location
- **US** A factor with levels No and Yes to indicate whether the store is in the US or not

# Sales of Child Car Seats

Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	US
9.50	138	73	11	276	120	Bad	42	17	Yes	Yes
11.22	111	48	16	260	83	Good	65	10	Yes	Yes
10.06	113	35	10	269	80	Medium	59	12	Yes	Yes
7.40	117	100	4	466	97	Medium	55	14	Yes	Yes
4.15	141	64	3	340	128	Bad	38	13	Yes	No
10.81	124	113	13	501	72	Bad	78	16	No	Yes
6.63	115	105	0	45	108	Medium	71	15	Yes	No
11.85	136	81	15	425	120	Good	67	10	Yes	Yes
6.54	132	110	0	108	124	Medium	76	10	No	No
4.69	132	113	0	131	124	Medium	76	17	No	Yes
9.01	121	78	9	150	100	Bad	26	10	No	Yes
11.96	117	94	4	503	94	Good	50	13	Yes	Yes
3.98	122	35	2	393	136	Medium	62	18	Yes	No
10.96	115	28	11	29	86	Good	53	18	Yes	Yes
11.17	107	117	11	148	118	Good	52	18	Yes	Yes

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- We are interested to predict car seat sales on the basis of the other variables.
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  - ▶ **Sales** variable as *target* (also called *response* or *output*) variable
  - ▶ **Price**, ....., **US** variables as *predictors* (also called *features* or *inputs*).



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## SUMMARY OUTPUT in R

Call:

```
lm(formula = Sales ~ ., data = Carseats)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.8692	-0.6908	0.0211	0.6636	3.4115

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	5.6606231	0.6034487	9.380	< 2e-16 ***
CompPrice	0.0928153	0.0041477	22.378	< 2e-16 ***
Income	0.0158028	0.0018451	8.565	2.58e-16 ***
Advertising	0.1230951	0.0111237	11.066	< 2e-16 ***
Population	0.0002079	0.0003705	0.561	0.575
Price	-0.0953579	0.0026711	-35.700	< 2e-16 ***
ShelveLocGood	4.8501827	0.1531100	31.678	< 2e-16 ***
ShelveLocMedium	1.9567148	0.1261056	15.516	< 2e-16 ***
Age	-0.0460452	0.0031817	-14.472	< 2e-16 ***
Education	-0.0211018	0.0197205	-1.070	0.285
UrbanYes	0.1228864	0.1129761	1.088	0.277
USYes	-0.1840928	0.1498423	-1.229	0.220

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.019 on 388 degrees of freedom

Multiple R-squared: 0.8734, Adjusted R-squared: 0.8698

F-statistic: 243.4 on 11 and 388 DF, p-value: < 2.2e-16

# Linear Regression

## SUMMARY OUTPUT in Excel

<i>Regression Statistics</i>					
Multiple R	0.93096584				
R Square	0.8666974				
Adjusted R Square	0.8632706				
Standard Error	1.04427131				
Observations	400				
ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	10	2758.069202	275.8069202	252.9172607	2.1457E-163
Residual	389	424.2054957	1.09050256		
Total	399	3182.274698			
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>
Intercept	2.99117944	0.630540793	4.743831753	2.94955E-06	1.751485123
CompPrice	0.09255237	0.004250367	21.77514872	2.5798E-69	0.084195802
Income	0.01615272	0.001889343	8.549386868	2.86354E-16	0.012438122
Advertising	0.12036692	0.011383601	10.57371215	3.87637E-23	0.097985836
Population	0.00029046	0.000379208	0.765975791	0.444155237	-0.00045509
Price	-0.0952477	0.002737379	-34.7952211	1.6832E-121	-0.100629614
Age	-0.0468605	0.00325562	-14.39373328	5.86807E-38	-0.053261339
Education	-0.020948	0.020210801	-1.036476421	0.300623799	-0.060684093
Urban_encoded	0.14120929	0.115711175	1.22036005	0.223067678	-0.086288254
US_encoded	-0.1293475	0.153069318	-0.845025443	0.398616061	-0.430294157
ShelveLoc_encoded	2.41157374	0.078399038	30.76024662	3.2204E-106	2.257434878

# Linear Regression in Excel

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- **Standard Error** of the regression: An estimate of the standard deviation of the error term  $\epsilon$ .
- **Observations.** Number of observations in the sample.

# Linear Regression in Excel

- Regression Sum of Squares:

$$(\hat{y}_1 - \bar{y})^2 + (\hat{y}_2 - \bar{y})^2 + \dots + (\hat{y}_n - \bar{y})^2 = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 = 2758$$

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- Residual Sum of Squares:

$$(y_1 - \hat{y}_1)^2 + (y_2 - \hat{y}_2)^2 + \dots + (y_n - \hat{y}_n)^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = 424$$

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- Total Sum of Squares:

$$(y_1 - \bar{y})^2 + (y_2 - \bar{y})^2 + \dots + (y_n - \bar{y})^2 = \sum_{i=1}^n (y_i - \bar{y})^2 = 3182$$

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**Note:** Total Sum of Squares = Regression Sum of Squares: + Residual Sum of Squares

- F: Overall F test for the null hypothesis:

$H_0$  : There is no relationship between predictors and the response  
versus the *alternative hypothesis*

$H_A$  : There is some relationship between predictors and the response

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Mathematically, this corresponds to testing

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_m = 0$$

$H_A$  : at least one  $\beta_j$  is non-zero.

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# F-statistic

This hypothesis test is performed by computing the F-statistic:

$$F = \frac{(\text{TSS} - \text{RSS})/m}{\text{RSS}/(n - m - 1)}$$

where

$$\text{RSS} = \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

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If the linear model assumptions are correct, one can show that

$$E [\text{RSS}/(n - m - 1)] = \sigma^2$$

and that, provided  $H_0$  is true,

$$E [(\text{TSS} - \text{RSS})/m] = \sigma^2$$

- Hence, when there is no relationship between the response and predictors, one would expect the F-statistic to take on a value close to 1.
- On the other hand, if  $H_A$  is true, then  $E[(\text{TSS} - \text{RSS})/m] > \sigma^2$ , so we expect F to be greater than 1.

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**$p$ -value**: the probability of observing any value equal to F-statistic or larger assuming there is no relationship between predictors and the response.

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- A small  $p$ -value (typically  $\leq 0.05$ ) indicates strong evidence against the null hypothesis, so you reject the null hypothesis (data are unlikely with a true null)
- A large  $p$ -value (typically  $> 0.05$ ) indicates weak evidence against the null hypothesis, so you fail to reject the null hypothesis (data are likely with a true null )



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This question can be answered by testing the hypothesis

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- The F-statistic can be used to determine whether or not we should reject this null hypothesis.
- The p-value corresponding to the F-statistic is very low, indicating clear evidence of a relationship between predictors and sales.

**Question** How strong is the relationship between predictors and sales?

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- This question can be answered by R-squared that tells us the percentage of variability in the response that is explained by the predictors.
- The predictors explain almost 93 % of the variance in sales.

**Question** How accurately can we estimate the effect of each predictor on sales?



# Sales of Child Car Seats

**Question** How accurately can we estimate the effect of each predictor on sales?

This question can be answered by the standard errors of coefficients to construct confidence intervals for each coefficient.

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 90.0%</i>	<i>Upper 90.0%</i>
Intercept	2.99117944	0.630540793	4.743831753	2.94955E-06	1.751485123	4.23087375	1.95155628	4.03080259
CompPrice	0.09255237	0.004250367	21.77514872	2.5798E-69	0.084195802	0.10090893	0.08554445	0.09956029
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- To answer this question, we can examine the p-values associated with each predictor's t-statistic.

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Intercept	2.99117944	0.630540793	4.743831753	2.94955E-06	1.751485123	4.23087375	1.95155628	4.03080259
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Price	-0.0952477	0.002737379	-34.7952211	1.6832E-121	-0.100629614	-0.0898658	-0.099761	-0.0907344
Age	-0.0468605	0.00325562	-14.39373328	5.86807E-38	-0.053261339	-0.0404597	-0.0522283	-0.0414927
Education	-0.020948	0.020210801	-1.036476421	0.300623799	-0.060684093	0.01878805	-0.0542712	0.01237515
Urban_encoded	0.14120929	0.115711175	1.22036005	0.223067678	-0.086288254	0.36870684	-0.049573	0.33199159
US_encoded	-0.1293475	0.153069318	-0.845025443	0.398616061	-0.430294157	0.17159922	-0.3817251	0.12303019
ShelveLoc_encoded	2.41157374	0.078399038	30.76024662	3.2204E-106	2.257434878	2.56571261	2.28231096	2.54083652

# Sales of Child Car Seats

## Question Which predictors contribute to sales?

- To answer this question, we can examine the p-values associated with each predictor's t-statistic.

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 90.0%	Upper 90.0%
Intercept	2.99117944	0.630540793	4.743831753	2.94955E-06	1.751485123	4.23087375	1.95155628	4.03080259
CompPrice	0.09255237	0.004250367	21.77514872	2.5798E-69	0.084195802	0.10090893	0.08554445	0.09956029
Income	0.01615272	0.001889343	8.549386868	2.86354E-16	0.012438122	0.01986733	0.01303761	0.01926783
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- The p-values for CompPrice, Income, Advertising, Price, Age, and ShelveLoc are low, but the p-value for Population, Education, Urban, US is not.
- This suggests that only CompPrice, Income, Advertising, Price, Age, and ShelveLoc.

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- 95% confidence interval is given by

$$\begin{aligned} & (13.64192 - 0.05307 \times \mathbf{Price} - 2 \times 2.525987, \\ & 13.64192 - 0.05307 \times \mathbf{Price} + 2 \times 2.525987) \\ & = (8.589946 - 0.05307 \times \mathbf{Price}, 18.69389 - 0.05307 \times \mathbf{Price}) \end{aligned}$$



# Sales of Child Car Seats

Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	US
9.50	138	73	11	276	120	Bad	42	17	Yes	Yes
11.22	111	48	16	260	83	Good	65	10	Yes	Yes
10.06	113	35	10	269	80	Medium	59	12	Yes	Yes
7.40	117	100	4	466	97	Medium	55	14	Yes	Yes
4.15	141	64	3	340	128	Bad	38	13	Yes	No
10.81	124	113	13	501	72	Bad	78	16	No	Yes
6.63	115	105	0	45	108	Medium	71	15	Yes	No
11.85	136	81	15	425	120	Good	67	10	Yes	Yes
6.54	132	110	0	108	124	Medium	76	10	No	No
4.69	132	113	0	131	124	Medium	76	17	No	Yes
9.01	121	78	9	150	100	Bad	26	10	No	Yes
11.96	117	94	4	503	94	Good	50	13	Yes	Yes
3.98	122	35	2	393	136	Medium	62	18	Yes	No
10.96	115	28	11	29	86	Good	53	18	Yes	Yes
11.17	107	117	11	148	118	Good	52	18	Yes	Yes

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- **Binary:** Is a US Store?
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  - **Ordinal:** ShelfLoc (Bad, Medium, Good)



# Binary Variables

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Examples:

- Is a US store?

$$x = \begin{cases} 1 & \text{if Yes} \\ 0 & \text{Otherwise} \end{cases}$$

- Is an Urban store?

$$x = \begin{cases} 1 & \text{if Yes} \\ 0 & \text{Otherwise} \end{cases}$$

# Nominal Variables

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Example:

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**Note:** Only  $K - 1$  dummies can (in general) be included, where  $K$  is the number of categories of the qualitative variable.