





## Machine Learning and Decision-Making

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- Linear Regression
- Hands On

Linear Regression (LR) is used when we want to predict the value of a variable (independent variable) based on the value of another variable (dependent variable).

It helps to determine if an independent variable does a good job in predicting the dependent variable or which independent variable plays a significant role in predicting the dependent variable.

- □ **Dependent Variable:** target variable that will be estimated and predicted (y);
- □ **Independent Variable:** predictor variable that is used to estimate and predict (x);
- $\square$  **Slope:** angle of the line, denoted as *m* or  $\theta$ 1;
- Intercept: where the function crosses the y-axis, denoted as b or  $\theta$ 0.

$$y = \beta 0 + \beta 1X + \epsilon$$

Linear regression finds the best fit line through your data by searching for the regression coefficient ( $\theta$ 1) that minimizes the total error ( $\varepsilon$ ) of the model.

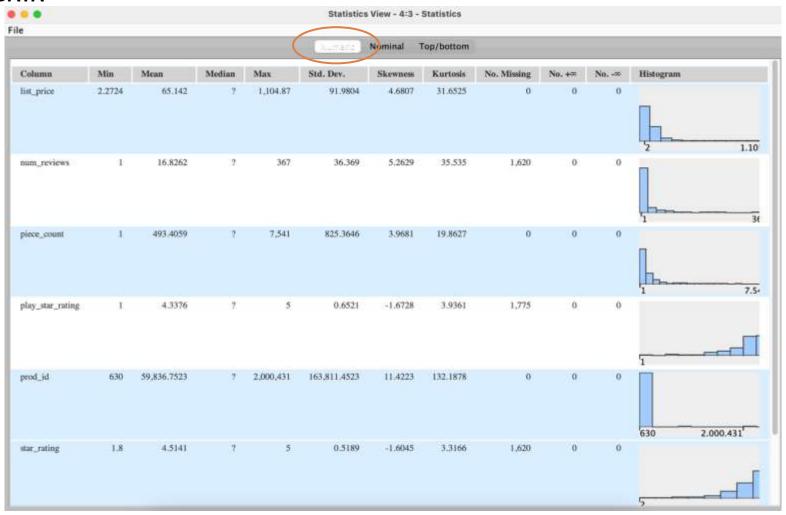
### Exercise:

- **Problem:** Development of a Machine Learning Model able to predict the price of a given LEGO set
- Regression Approach: Linear Regression approach to solve this problem
- Dataset: Table with information regarding LEGO sets, containing:
  - 'age': Which age category it belongs to
  - 'list\_price': Price of the set (in \$)
  - 'num\_reviews': Number of reviews per set
  - 'piece\_count': Number of pieces in that LEGO set
  - 'play star ratings': Ratings
  - 'review\_difficulty': difficulty level of the set
  - 'star\_rating': Ratings
  - 'theme name': Which theme it belongs
  - 'val\_star\_rating': Ratings
  - 'country': Country name

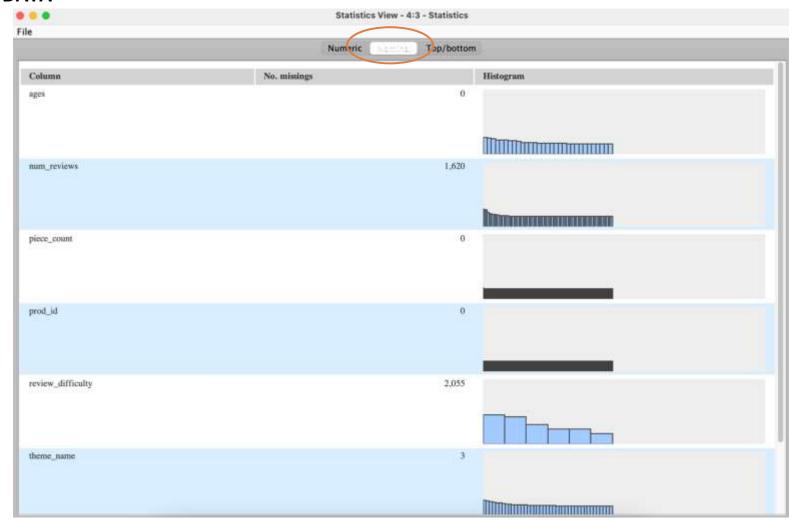
### **CHECK OUT THE DATA**

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Row ID	S ages	D list_pr.	1 num_r	I piece	D play_s	I prod_id	S review	D star_r	S theme	D val_st	S country
Row0	6-12	29.99	2	277	4	75823	Average	4.5	Angry Birds™	4	US
Row1	6-12	19.99	2	168	4	75822	Easy	5	Angry Birds™	4	US
Row2	6-12	12.99	11	74	4.3	75821	Easy	4.3	Angry Birds™	4.1	US
Row3	12+	99.99	23	1032	3.6	21030	Average	4.6	Architecture	4.3	US
Row4	12+	79.99	14	744	3.2	21035	Challenging	4.6	Architecture	4.1	US
Row5	12+	59.99	7	597	3.7	21039	Average	4.9	Architecture	4.4	US
Row6	12+	59.99	37	598	3.7	21028	Average	4.2	Architecture	4.1	US
Row7	12+	49.99	24	780	4.4	21029	Average	4.7	Architecture	4.3	US
Row8	12+	39.99	23	468	3.6	21034	Average	4.7	Architecture	4.1	US
Row9	12+	39.99	11	444	3.6	21033	Average	4.8	Architecture	4.5	US
Row10	12+	39.99	14	386	4.1	21036	Average	4.4	Architecture	3.6	US
Row11	12+	34.99	53	321	3.2	21019	Average	4.6	Architecture	4.4	US
Row12	12+	29.99	7	361	4.2	21032	Easy	4.6	Architecture	4.2	US
Row13	7-12	159.99	63	847	3.8	17101	Average	3.4	BOOST	3.5	US
Row14	10+	29.99	13	708	4.7	41597	Average	4.8	BrickHeadz	4.8	US
Row15	10+	19.99	1	234	3	41614	Easy	5	BrickHeadz	5	US
Row16	10+	19.99	1	160	5	41613	Very Easy	5	BrickHeadz	5	US
Row17	10+	9.99	1	149	2	41609	Very Easy	3	BrickHeadz	4	US
Row18	10+	9.99	1	141	2	41608	Very Easy	4	BrickHeadz	4	US
Row19	10+	9.99	3	101	4	41604	Average	4.7	BrickHeadz	4.5	US
Row20	10+	9.99	2	105	3	41605	Easy	5	BrickHeadz	5	US
Row21	10+	9.99	1	113	5	41606	Easy	5	BrickHeadz	5	US
Row22	10+	9.99	1	136	?	41607	?	5	BrickHeadz	7	US
Row23	10+	9.99	2	91	3	41485	Easy	4.5	BrickHeadz	4	US
Row24	10+	9.99	7	140	3.2	40270	Easy	4.9	BrickHeadz	4.7	US
Row25	10+	9.99	5	143	4.6	41599	Easy	5	BrickHeadz	5	US
Row26	10+	9.99	3	122	2.7	41598	Very Easy	4	BrickHeadz	3	US
Row27	10+	9.99	5	130	4.3	41603	Easy	5	BrickHeadz	4.8	US
Row28	10+	9.99	3	119	4.5	41602	Easy	5	BrickHeadz	4.5	US
Row29	10+	9.99	1	135	1	41600	Very Easy	4	BrickHeadz	3	US

### **CHECK OUT THE DATA**



### **CHECK OUT THE DATA**

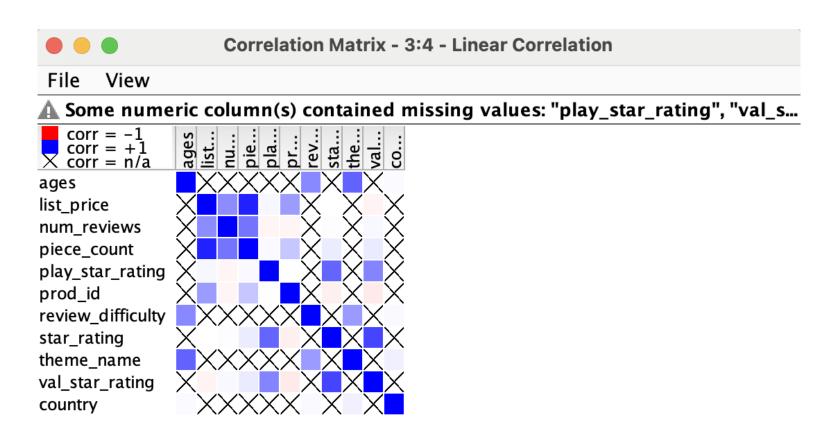


#### **COLUMN FILTER**

We can drop the product ID from our data

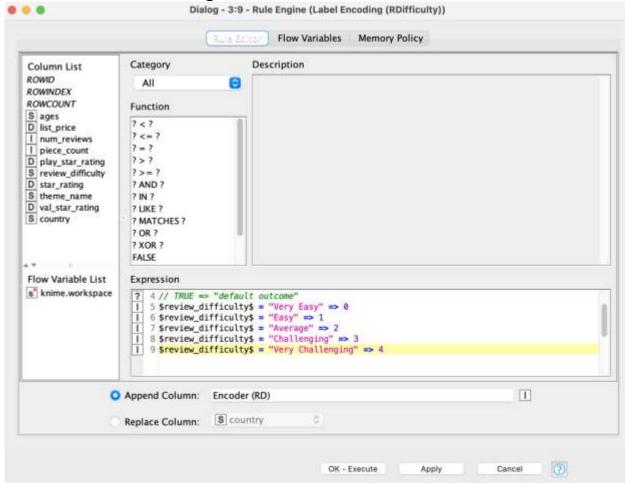


### **CORRELATION STUDY**



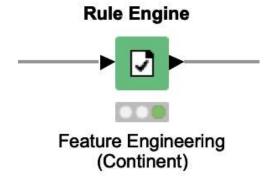
### **ENCODING**

### **Label Encoding**



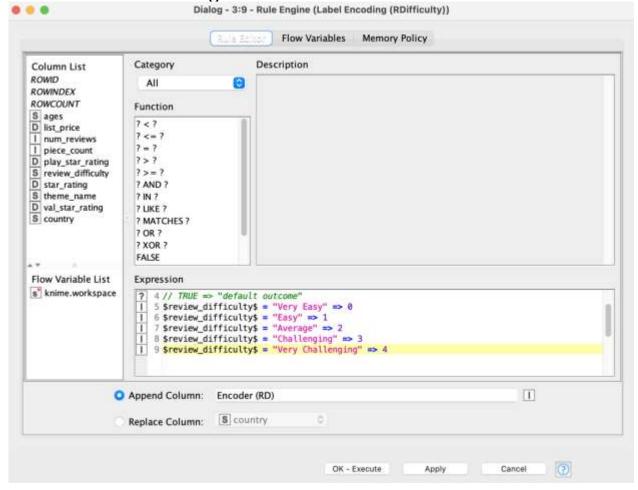
- Can we do one-hot encoding to all our left columns? Does it make sense?
- Remember: encoding a huge number of categories has a very high cost...



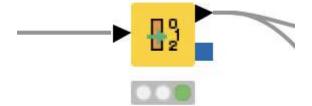


### **ENCODING**

**Label Encoding** 



### **Category To Number**

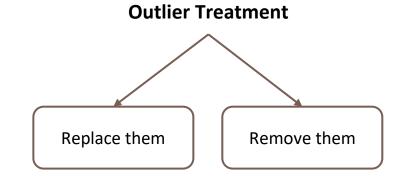


Map Categorical values to Numerical

### **OUTLIERS**

Now, our dataset is in a numerical format  $\overset{\circ}{\otimes}$ Next step: treat any **numeric** outliers that may exist Outliers are extreme values in a feature that deviate from other observations on data. They need to be treated as they may have an effect on the statistics involved in the data.

# Numeric Outliers Remove outliers

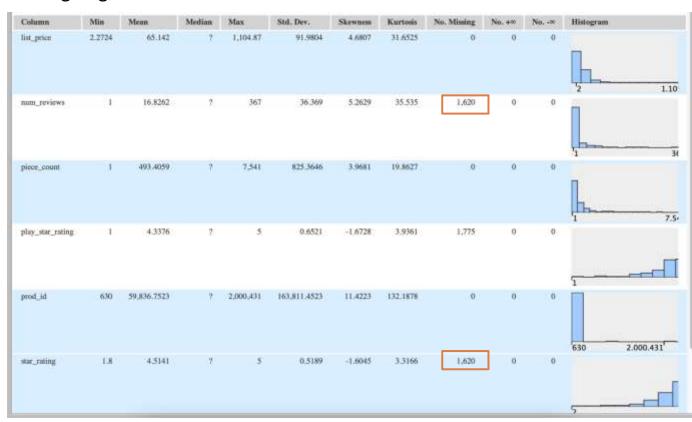


It mainly depends on the quantity of outliers.

### **MISSING VALUES**

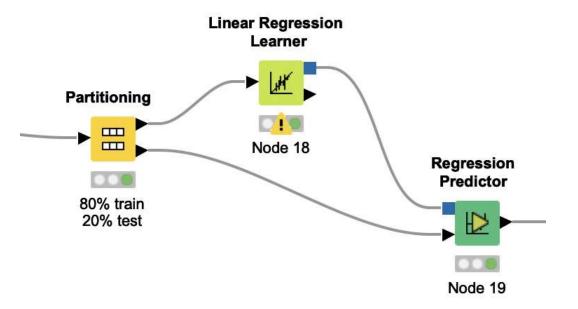
We still have a lot of missing values in our data. What are we going to do about it?

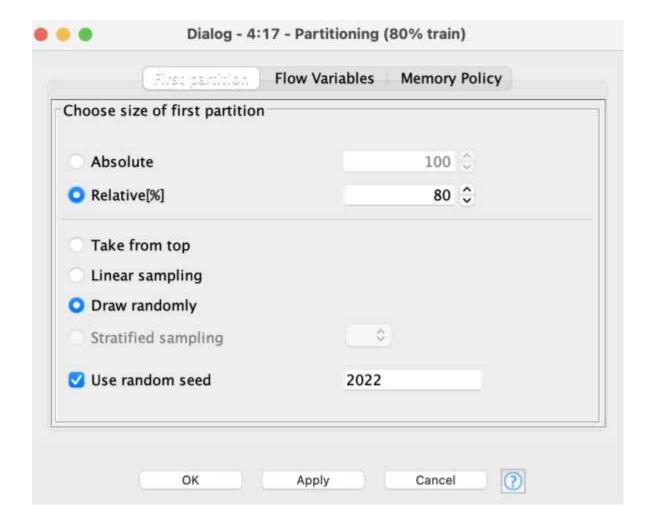
- 1) Mean
- 2) Median
- 3) Most used Value
- 4) Business knowledge and Knowledge extraction



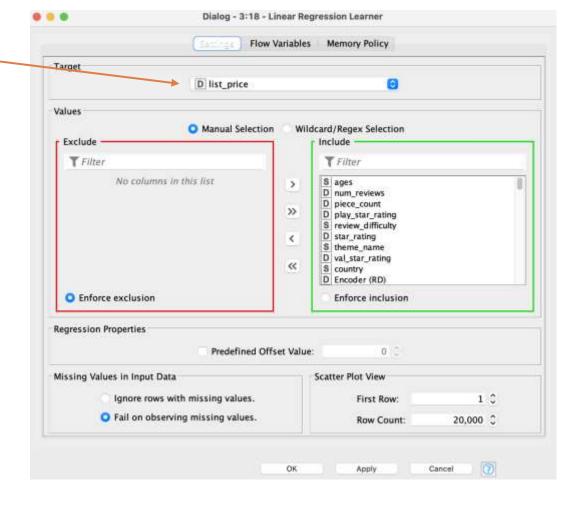
### TRAINING A LINEAR REGRESSION MODEL

Label: LEGO set price





## TRAINING A LINEAR REGRESSION MODEL Label: LEGO set price **Linear Regression** Learner **Partitioning** Ш Node 18 Regression **Predictor** 80% train 20% test Node 19



### **EVALUATING THE MODEL**

- 1. R-Square value
- 2. Mean Absolute Error (MAE)
- 3. Mean Square Error (MSE)
- 4. Root Mean Square Error (RMSE)

**R-Squared**: proportion of variation in the outcome that is explained by the predictor variables.

## total variance explained by model total variance

Here, the higher the value, the better the model. 1 means that the model explains 100% of the variance of the labels. 0 means that the model doesn't understand how the labels vary.

**MAE:** mean of the absolute value of the errors  $\frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$ 

$$\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i|$$

**MSE:** mean of the squared errors

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

### **EVALUATING THE MODEL**

- 1. R-Square value
- 2. Mean Absolute Error (MAE)
- **3.** Mean Square Error (MSE)
- 4. Root Mean Square Error (RMSE)——

**RMSE:** calculates the average of the square roots of the error between values (actual) and predictions (hypotheses). It has a range from 0 to infinity and returns the magnitude of errors. The scores are negatively-oriented, so **lower values are better.** A score of 0 means that, on average, the predictions are great, that is, 100% effective.

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

Comparing the MAE, MSE and RMSE metrics:

- MAE it's the easiest to understand because it's the average error;
- MSE it's most popular than MAE because MSE "punishes" larger errors, which tends to be useful in real world problems;
- **RMSE** is even more popular than MSE because RMSE is interpretable in the "y" units.

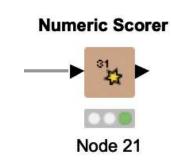
All of these are **loss functions**, so we want to minimize them.

### **EVALUATING THE MODEL**

- 1. R-Square value
- 2. Mean Absolute Error
- **3.** Mean Square Error
- 4. Root Mean Square Error (RMSE)

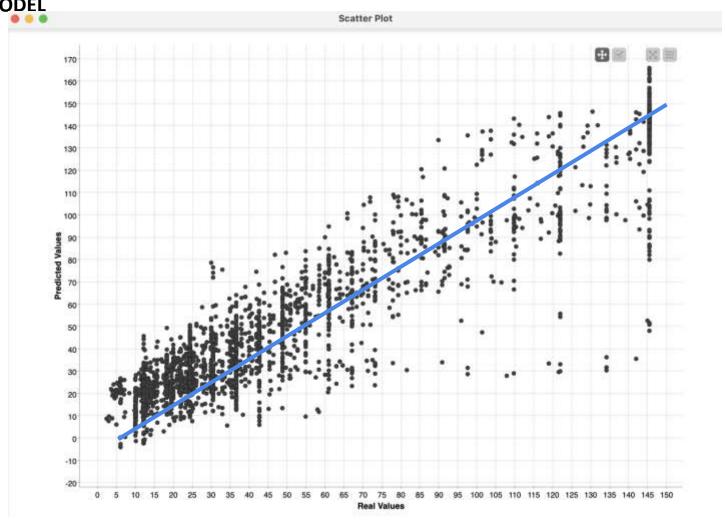
Knime's **Numeric Scorer** takes the predicted feature values and actual feature values as input and produces the metrics.

Our model has an R-square value of 74.4 % which means that 74.4% of our lego dataset falls around the regression line created by our model.



• • •	Statistics - 3:21 - Numeric Scorer					
File						
	R <sup>2</sup> :	0.744				
	Mean absolute error:	9.33				
	Mean squared error:	230.695				
	Root mean squared error:	15.189				
	Mean signed difference:	0.079				
	Mean absolute percentage error:	0.283				
	Adjusted R <sup>2</sup> :	0.744				

### **EVALUATING THE MODEL**



### **EVALUATING THE MODEL**

