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Student Name:	Rasikh Thakur			
Student ID:	W23042021			
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#### **Submission Instructions**

- Name your submission in according to the name convention, <module number>\_<tutor initial>\_< prog code>\_<assignment group>\_<your id><first name>.docx, eg
   LD7087\_NT\_BD\_A\_w22012345John.docx is the LD7087 assignment submitted from a group A student enrolled in MSc Big Data & Data Sciences, attending Ning Tse's session.
- 2. Submit to Final Submission Link on Bb before 16:00, 23 Jan 2024

#### Declaration

I confirm that this assessment is my own work and that I have duly acknowledged and correctly referenced the work of others. I am aware of and understand that any breaches to the Code of Academic Conduct will be investigated and sanctioned in accordance with the Academic Conduct Regulation.

Your signature:	Rasikh Sadiq Thakur	Date:	21/01/2024
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Task one: Domain Understanding and Research Questions

The data set is relevant to the area of real estate and housing market research, focusing on

residential property transactions in London. This subject encompasses the research fields

housing market dynamics, urban studies and real estate economics. Scholars in this field

discuss several aspects, including property prices, modalities of transactions and product

types as well as factors influencing housing market. The dataset contributes to the knowledge

on dynamics occurring in real estate and provides valuable data for analysis of patterns, as

wells trend forms within London' housing markets.

Paper studied:

First Paper:

Paper Name: Deep Learning Model for House Price Prediction Using Heterogeneous Data

Analysis Along With Joint Self-Attention Mechanism

Authors: PEI-YING WANG1, CHIAO-TING CHEN 2, JAIN-WUN SU1, TING-YUN

WANG1, AND SZU-HAO HUANG 3, (Member, IEEE) 1 Institute of Information

Management, National Chiao Tung University, Hsi

Analysis:

Research Problem:

This work tackles the issue of inaccurate house price forecasts in previous research because

of incomplete data. It emphasises how crucial it is to take into account both the

environmental aspects of the immediate area and the home itself.

**Proposed Solution:** 

An end-to-end joint self-attention model for predicting property prices is put out by the

authors. The model uses satellite maps to analyse the surrounding area and integrates data on

public amenities (parks, schools, etc.). Attention methods are used to pinpoint important

aspects that potential customers are thinking about.

Important Elements of the Model:

2

An attention mechanism and a spatial transformer network (STN) are employed by the model

to manage heterogeneous data, such as data from public facilities and satellite maps. From

satellite maps, the STN extracts rotation-invariant picture characteristics.

Information Used:

The experimental data consists of satellite maps acquired via the Google Maps API, actual

selling prices from real estate transactions in 2017 and 2018, and data from Taipei and New

Taipei governments on public facilities.

Comparing This Model with Others:

The performance of the suggested model is contrasted with that of several machine learning-

based models, including deep learning, numerous attention models, Extreme Gradient

Boosting, and Light Gradient Boosted Machine.

Results of the experiment:

The experimental findings show that the suggested model works better than other models and

achieves a low prediction error. According to the authors, this model is the first to predict

home prices using both a STN network and an attention mechanism.

Contributions:

The primary innovations include the inclusion of a joint self-attention mechanism taking into

account two-hop correlations between various variables, the incorporation of heterogeneous

data, and the use of STN for picture feature extraction.

Novelty:

The research highlights its innovation by asserting that it is the first to combine STN network

and attention processes for predicting housing prices.

**Second Paper:** 

Paper Name: Boston House Price Prediction Using Regression Models

3

Authors: Saptarsi Sanyal, Saroj Kumar Biswas, Dolly Das, Manomita Chakraborty, Biswajit Purkayastha

# Analysis:

Use machine learning algorithms to give reliable predictions on the housing values. The researchers used Ridge Regression, Lasso Regression, Polynomial regressions and Simple Linear Regression with the Boston Housing dataset. The models were evaluated using metrics such as R-Squared, Root Mean Square Error (RMSE), and Cross Validation.

#### Model Execution:

Among the models, Lasso Regression performed better than all others achieving maximum accuracy in R – Squared and Cross-Validation.

Ridge Regression did well also; and it had the second highest accuracy.

A two regression of polynomial degree outperformed simple linear regressions; however, it did not perform as well as a Lasso and Ridge Regression.

# Pre-processing of Data:

The application of good prediction techniques such as outlier removal and log transformation requires data pre-processing procedures.

Strong correlations between features like "TAX" and "RAD" point to the need to eliminate unnecessary characteristics in order to increase model efficiency.

### Future work:

By gathering more current data, the research may be expanded to take into consideration shifts in the real estate market over time.

Further insights may be obtained by evaluating other machine learning models, such as ensemble approaches, decision trees, and support vector machines.

To improve model performance, feature selection strategies and optimisation techniques, such as deep learning approaches, might be investigated.

### In summary:

The paper's models can be used as a starting point to forecast home prices.

To increase forecast accuracy, further study and advancements—including the use of cuttingedge models and methods—are necessary.

# **Research Questions:**

1. Do the average home prices in London's boroughs differ much from one another? Examining regional differences in housing costs is one such area of investigation.

Null Hypothesis (H0):

The average cost of a home in each given London borough does not differ much from one another.

Theoretically: H0:  $\mu$  borough1 =  $\mu$  borough2 =... =  $\mu$  boroughN

Alternate hypothesis (Ha):

There exists a notable disparity in the mean property values between a minimum of two London boroughs.

Symbolically: Ha: Among the  $\mu$ \_boroughs, at least one is not like the rest.

2. Does the kind of property (home, flat, etc.) affect the London real estate market price in a statistically meaningful way?

Examining if property type affects pricing might be one area of study.

Null Hypothesis (H0):

The type of property in London has no discernible impact on the selling price.

H0:  $\mu$  apartment =  $\mu$  house, symbolically

Alternate hypothesis (Ha):

The type of property in London has a substantial impact on the selling price.

Ha:  $\mu$ \_apartment  $\neq \mu$ \_house, symbolically

3. Does the kind of estate—freehold or leasehold—have a big influence on how much a London property sells for?

Null Hypothesis (H0):

The selling price of homes does not significantly change depending on whether they are leasehold or freehold.

H0:  $\mu$  freehold =  $\mu$  leasehold, symbolically

Alternate hypothesis (Ha):

The selling price of houses varies significantly depending on whether they are leasehold or freehold.

Ha:  $\mu$ \_freehold  $\neq \mu$ \_leasehold, symbolically

#### **References:**

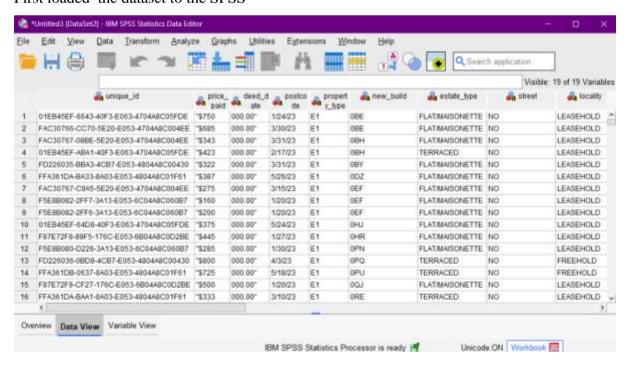
IEEE Xplore Full-Text PDF: (no date).

https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9395585.

https://www.researchgate.net/publication/362812590 Boston House Price Prediction Using Regression Models

### Task two: Dataset and Data Preparation

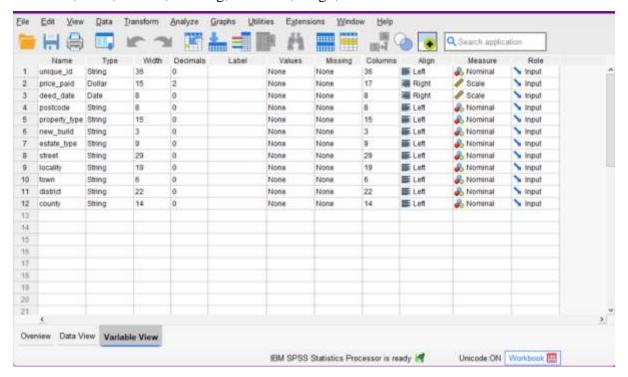
First loaded the dataset to the SPSS



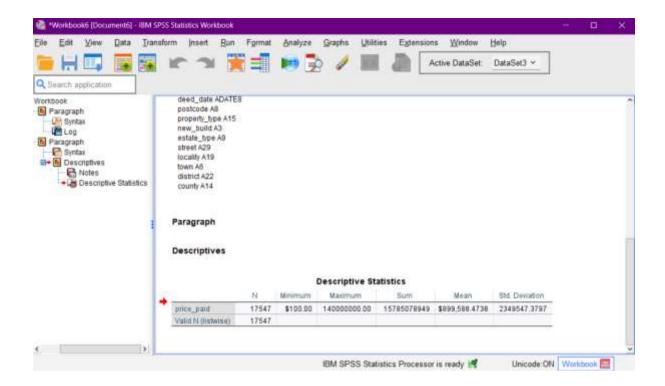
Now after loading the dataset in the SPSS, exploring the dataset.

Now in the SPSS, clicked on the variable view where we can see the information about each column in the dataset.

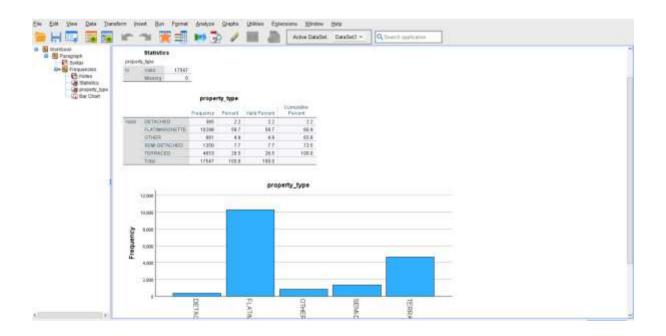
As we can see in the below image, the dataset every variable name, variable type, width, Decimals, label, Values, Missing, Columns, Align, measure and Role.



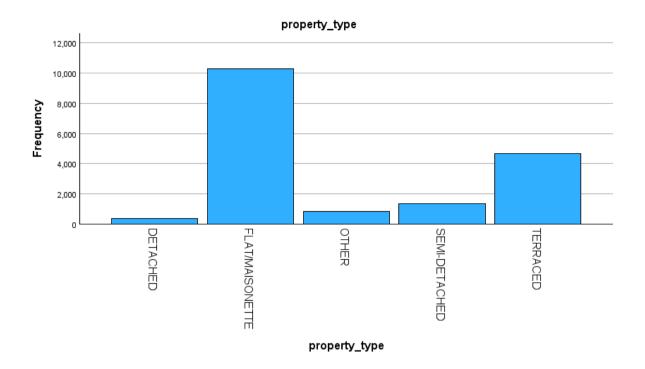
Then calculated the descriptive statistics. So from the above when explored the dataset we can see that of the variable price\_paid as its type is dollar so we can calculate the descriptives i.e Mean, median, Sum ,Standard Deviation, Maximum, Total Count (N).



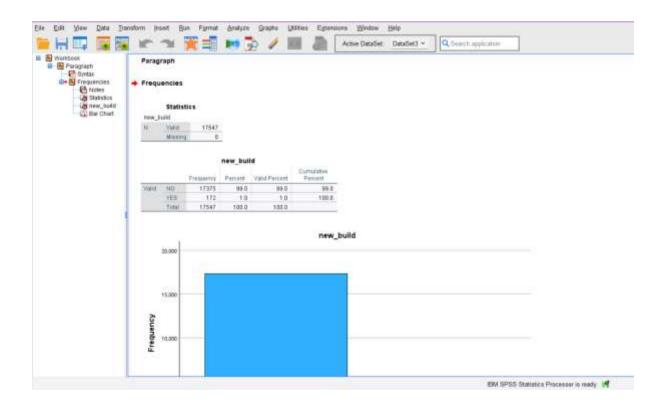
And then for the variable property\_type we are calculating the statistics, then for the property\_type variable where we have DETACHED, FLAT/MAISONETTE, OTHER,SEMI-DETACHED, TERRACED. So for each of this shows the Frequency, Percent, valid Percent, and Cumulative Percent.

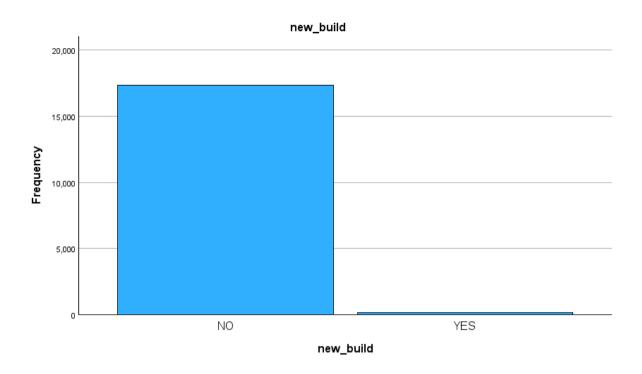


Also plotted the bar chart for the property\_type variable.



Similarly for the new\_build variable also we are plotting the bar chart and calculated the statistics, Frequency, percent, Valid Percent, Cumulative Percent.

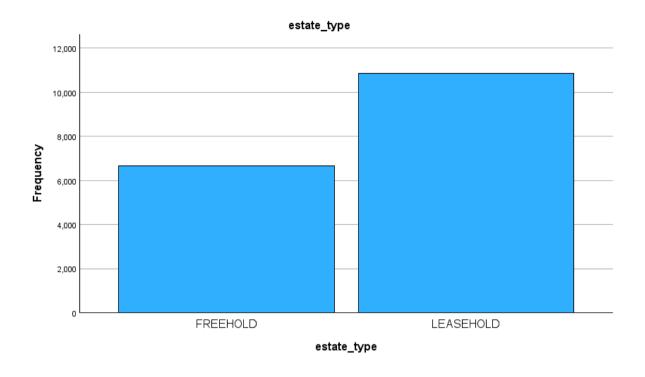




Similarly, for esate\_type variable we have calculated the statistics and Frequency, Percent, valid percent, and Cumulative Percent for both the type i.e for FREEHOLD and LEASEHOLD of the estate\_type.

estate_	_type				
N	Valid	17547			
	Missing	0			
		est	tate_type		
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	FREEHOLD		V-05.8	Valid Percent	Percent
Valid	FREEHOLD	Frequency 6678	Percent	THE STATE OF THE S	

And also plotted the bar chart for estate\_type.



**Task three: Data Analytical Methods** 

# So now for first research question:

Do the average home prices in London's boroughs differ much from one another?

T discourances				Descripti	V#9			
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01/00/23	362	\$787,518,8113 \$880,000,000	1000/42/643/	\$62,037 81000	\$683.062.9701	\$911,370,0524	\$101,003.00 \$800,000.00	16260000 00 8400,000 00
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01/30/23	149	\$907.089.0021 \$990.912.9464	31704783578 1314315.9913	182256 96902 \$75,158 08304	\$640,002 3221 \$818,916,8100	1207977 4821	\$610.00 \$25,000.00	24700000 00 10700000 00
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92/27/23	123	\$216,500,0000 \$885,203,4585	1291984.0973	100526,09764	\$690,529,1110	1109979.8055	\$218,600 00 \$90,000 00	10750000 00
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00/01/23 04/01/23	502	\$939.070,4801 \$680,900,0000	1549396,1536	\$69,152,93463	\$002,204,9955	1074935.9646	\$15,000.00	1000000000
04/03/24 04/03/27	100	11 50000 0000 \$880.11 8 1 207	1224327.0029	109782 37770	*********	1000205.4332	\$1,150,000.00 \$100,000.00	\$1,150,606.00 1,2500000.00
04/04/29 04/05/23 04/06/23	150	\$703.057.0733 \$723.117.4190	######################################	\$25,515,37987 \$62,606,97733	\$632.079.0147	\$779.236.2320	\$74,000.00	\$2.550,000.00
94/99/24 94/11/23	179	\$389.354.0000 \$689.607.7009	1015571.8588	123188.31880	\$690.178.8930 \$593.762.7169	1000452:0902	\$98,000.00 6369,354.00 8169,000.00	\$9,520,000.00 \$369,354.00 \$9,100,000.00
94/13/23 94/13/23	62	\$693,873,046A 1887849,7317	428650 37128 3667119.3480	\$43,070 03280 404080 58590	\$606.369.1760 \$662.080.2440	9779.344.0000 2193595.2194	\$120,000 00 \$142,500 00	\$7,100,000.00 37580000.00
04/14/20	240	\$640,500,0000	31 W. S.	\$50,201 DASHO	8773.009.1207	100001122127	\$30,600.00 6540,500.00	\$7,500,000.00 8640,500.00
04/16/23 04/16/23	66	\$040,770,0025 \$700,000,3333 \$001,462,3924	1147133,2988 822802,96970	117078 80214 \$70,503 20543 131574 19211	\$616.345.7631 \$636.060.6338 \$599.510.2977	1891207.3719 \$903.065.7331 7123486.4071	\$130,000.00 \$19,000.00	\$4,109,000.00 16200000.00
04/20/23	229	\$763.008 1379 \$605 223 6333	887836 21218 1307963 4920	\$73,754.36643 \$62,665.36366	\$000 300 2504 \$630 703 0400	1004854 8180	\$260,000.00 \$69,294.00 \$29,250.00	\$6.300,600.00 2000,000.00
04/24/23 04/25/22	6.7	\$603.917.4187 \$603.028.6966	870288 28224 809600 41740	102850 46929 \$74,478.04301	\$677,923,7484 \$655,231,4001	1886717.8911	\$190,000 00 \$200,000 00	\$6,000,000.00 \$3,400,001.00
94/20/23 84/27/24	6.6	1203228.2100	095293 59534 6426162,3413	112049.19964	\$541.050.7665 \$319.947.8488	\$900.075.6770 2184005.4281	\$02,000.00 \$2,000.00	\$5.550,606.00 4.2060606.00
04/20/29 00/93/74 08/03/29	360 88	1040,015,6361 1888,460,6510 1028410,4478	#34090 21514 #398#1 710#4 1013000 4717	\$43,007 24069 \$84,537 91969 197087 80167	\$756.510.0948 \$720.888.3884 \$634.961.8889	1050264 7216 1421869.8076	81,000 00 8162,000 00 8101,600 00	\$6,500,000.00 \$6,200,000.00 16560000.00
95/94/93 96/96723	909	\$752,328.1125 1036821,1871	561839 92167 2476339,4860	171601 02317	\$627.284.7849 \$697.363.1323	1077.357.4401	\$70,000 00 \$1,000 00	\$3.200,000.00 32800000.00
06/09/23 #8/76/24	05 WJ	1234200.9305 \$802.842.0217	3001509.6107 12072081989	434318 72560 134290 73164	\$350.637.5409 \$696.289.2043	2091940,3200 1229410,7982	\$75,000.00 \$160,000.00	\$6,000,000.00
06/11/23 06/13/23 06/13/23	192	\$667,877,6366 \$782,472,6510 \$578,768,0000	785926 02782 111389 31804	158041,73025 868,676,02420	\$648.524.0496 \$670.081.9476	9894 263 9545 1678363 6230	\$140,000 00 \$140,000 00	12000000 00 \$8.500,000 00
95/15/23 86/15/23	102	1027.945.3027 1788.832.0243	044137.95959 1239169.0349	\$78,750 00000 \$93,493 56009 188874 77318	4218636230 \$6+2,499,6760 \$477,773,4488	1013361.6547	\$96,000.00 \$180,000.00	\$6.700,000.00 11780000.00
99/17/23 99/19/23	92 73	\$751.500.0070 \$920.780.7945	905190.26992 12762611567	364,051,19494 149323 NBW4W	\$594,581,3237 \$623,009,3681	1218502 2210	\$2,000.00 \$104,000.00	\$6,690,000.00
06/23/23	225 90	\$690,431,6933 \$729,119,9322	520353 15751	\$36,746,17632 \$54,650,03965	\$618,021,2461 \$614,124,4634	\$762,842 1406 \$632,095 161+	\$122,600.00 \$1.00.00	\$4,860,000.00 \$9,325,000.00
86/24/23 86/24/23 86/28/23	99 131	\$700.370.0000 \$910.474.5714	002904 59460 892819 02909	129279.88489 \$61,105.61196	\$448.410.6703 \$749.502.3039	1071446,7600 2016901,8936	\$190,000.00 \$195,000.00	\$6.425,000.00 \$6.425,000.00
06/20/23	266	\$902.476.4188 \$767.836.6267 \$628.000.0000	744661 67105	\$78,000 96000	\$681 377 7757	\$854,465,8817	\$139,000,00 \$01,676,00 \$525,000,00	\$7,175,000.00 \$7,175,000.00 \$525,000.00
D6130423	119	\$430,000,0000 \$654,003,5714	87,671 06781 1096222,2940	81,000 00000 100491 44972	\$356.488.0763 \$655.003.1442	\$483,633,023T 1052003,0006	\$155,000.00 \$155,000.00	8425,000 00 10000000 00
06/01/27	133	\$790,317,6917	043622.03715	\$65,600 16053	\$784,581,2000 \$688,921,6559	3163045.7948 \$809.713.7275	\$78,000.00 \$78,000.00	\$9,400,000.00
98/02/23 98/98/23 98/98/23	78	1881 118 9872 1811178 4722	739674 00637 1734333 3593	\$63,751.00021 204302.14863	\$611,285,0000 \$664,366,3471 \$603,630,1133	10170H7.72F2 1719738 8313	\$80,000.00 \$80,000.00 \$290,000.00	\$6,469,000.00 \$6,469,000.00 \$9,309,090.00
36/07/23 36/00/23	80 67	\$694.891.6925 \$746.411.6322	462644 20939 865490 79626	\$70,274,91700	\$694 182 7619 \$606 709 7192	\$796.800.3631 \$606.113.5451	\$109,000.00 \$140,000.00	\$2 700,000.00 \$5 260,000.00
00/09/23	245	1290000,0000	800000 72003	\$61,694,65162	\$716.731.9030	9020,341,5020	\$65,000.00 \$1,295,000.00	\$9.309,606.06 \$1.299,606.06
0674 272 A 0674 3757 A	60 60 7.4	\$794.154.6168 \$813.523.3314 \$943.555.2973	771445.90702 1061492.6363 780434.65119	\$61,772.0020W 141847.01000 \$90,722.08570	\$631 647.8797 \$620 262 7374 \$762 738 3531	\$850,681,3540 1092781,8004 1124362,3416	\$141,250.00 \$5,000.00 \$195,000.00	\$6,359,696.90 \$6,969,696.96
0471 4723 0471 6723 0471 6723	103	\$903.460.6735 \$361467.7068	1020802 5434 4453900 7014	161093 92130 260097 31405	9702.997 8337 9702.997 8337	1103963 8114 1806866 3610	\$78,000.00 \$78,000.00	\$7.865,000.00 \$7.865,000.00 \$2960000.00
06/16/23	91 70	\$782.405,4835 2774568.7867	023474 23599 10992042 328	1011474.4720	\$603.560.5003 -1038727.330	9913.250.2017	\$150,000.00 \$178,000.00	\$4.115,600.00 134560600.00
00/21/22	2.1	#721.000 1549 #875.362.6512	515830 92919 834326 52288	\$61,317,00000 \$80,007,74270	\$699,583,8660 \$696,472,6750	\$843,784,3439 1854232,8287	\$100,000.00 \$100,000.00	\$2,760,000.00 \$6,380,000.00
00/24/23	3 91	\$203,219,0000	140873.76493	\$77,483 71943 \$61,196 30163 646603 66697	\$823.585.7662 -\$35.965.5907 \$163.666.2860	3612,423,5907 2730460,3594	\$68,946.00 \$137,600.00 \$30,000.00	\$415,000.00 \$415,000.00
06/27/23	73	1447063.3077 \$903,705,6712 \$888,864,4235	#182473.8824 1042320.2107 802331 37085	121994.35414 887,871.57870	\$193.968.3680 \$600.594.3709 \$730.038.8880	2738480.3684 2148976.8715 2884282.7817	\$40,000.00 \$40,000.00	\$6.900,000.00 \$6.900,000.00
00/30/23	305	1000001.8723	2070882,7229	213690 24360 173671 72660	\$632,783.6488 \$656.094.4386	1481108 1952	\$100,600.00	17760000 00 36840000 00
07/03/23 07/04/23	49	\$601 010 3182 \$670,235.1027	487708 86741 868920 79131	\$40,791 80616 124131 54162	\$620.651.9910	\$778,868,4981 1119010,3750	\$65,000.00	\$4.425,000.00
0.450.6454 0.450.6454	63 55	\$646,303,0364 \$842,201,2804	810036 03922 804024 27621 771647 81564	\$66,600 04178 112527 23045 \$72,618 74187	\$619,700,1227 \$619,700,1227	10/0907 1500	\$167,000.00 \$167,000.00 \$168,000.00	\$4,500,000.00 \$6,500,000.00

#### ANOVA

#### price\_paid

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.118E+15	152	7.358E+12	1.337	.004
Within Groups	9.574E+16	17394	5.504E+12		
Total	9.686E+16	17546			

# ANOVA Effect Sizes a,b

			95% Confidence Interval	
		Point Estimate	Lower	Upper
price_paid	Eta-squared	.012	.001	.006
	Epsilon-squared	.003	008	003
	Omega-squared Fixed- effect	.003	008	003
	Omega-squared Random- effect	.000	.000	.000

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

As from the ANNOVA we can see that we got the Sig. value as 0.004 which is less than 0.005 so we can reject the Null hypothesis.

### Null Hypothesis (H0):

The average cost of a home in each given London borough does not differ much from one another.

Theoretically: H0:  $\mu$  borough1 =  $\mu$  borough2 =... =  $\mu$  boroughN

### Now for the Second Research Question:

Does the kind of property (home, flat, etc.) affect the London real estate market price in a statistically meaningful way?

Examining if property type affects pricing might be one area of study.

In order to examine if the kind of property (house, flat, etc.) influences the price of real estate in London, we may run an Kruskal-Wallis test. The Kruskal Wallis test is suitable for ordinal and nominal data.

b. Negative but less biased estimates are retained, not rounded to zero.

#### **Hypothesis Test Summary**

Null Hypothesis	Test	Sig. <sup>a,b</sup>	Decision
The distribution of price_paid is the same across categories of property_type.	Independent-Samples Kruskal- Wallis Test	<.001	Reject the null hypothesis.

- a. The significance level is .050.
- b. Asymptotic significance is displayed.

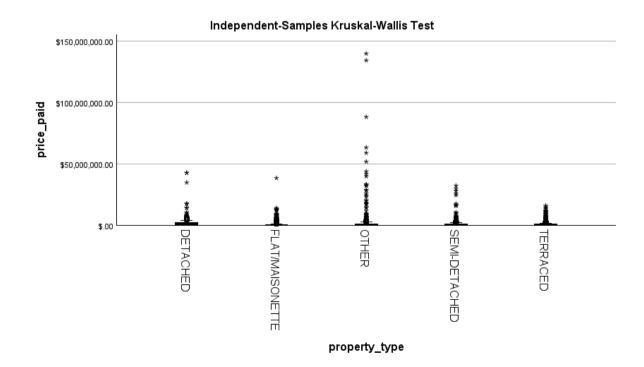
# Independent-Samples Kruskal-Wallis Test

# price\_paid across property\_type

# Independent-Samples Kruskal-Wallis Test Summary

Total N	17547
Test Statistic	3234.539 <sup>a</sup>
Degree Of Freedom	4
Asymptotic Sig.(2-sided test)	<.001

a. The test statistic is adjusted for ties.



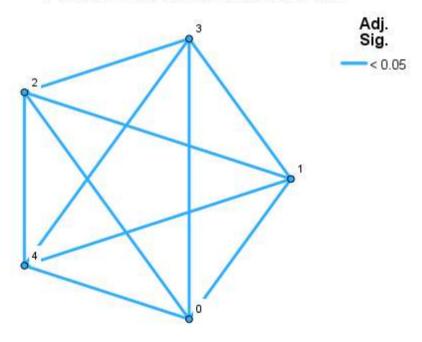
# Pairwise Comparisons of property type

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig. <sup>a</sup>
FLAT/MAISONETTE- OTHER	-1237.784	179.703	-6.888	<.001	.000
FLAT/MAISONETTE- TERRACED	-3979.150	89.477	-44.471	<.001	.000
FLAT/MAISONETTE-SEMI- DETACHED	-5210.031	146.623	-35.533	<.001	.000
FLAT/MAISONETTE- DETACHED	7342.151	262.942	27.923	<.001	.000
OTHER-TERRACED	-2741.366	187.925	-14.588	<.001	.000
OTHER-SEMI-DETACHED	-3972.247	220.926	-17.980	<.001	.000
OTHER-DETACHED	6104.368	310.561	19.656	<.001	.000
TERRACED-SEMI- DETACHED	1230.881	156.592	7.860	<.001	.000
TERRACED-DETACHED	3363.002	268.629	12.519	<.001	.000
SEMI-DETACHED- DETACHED	2132.120	292.666	7.285	<.001	.000

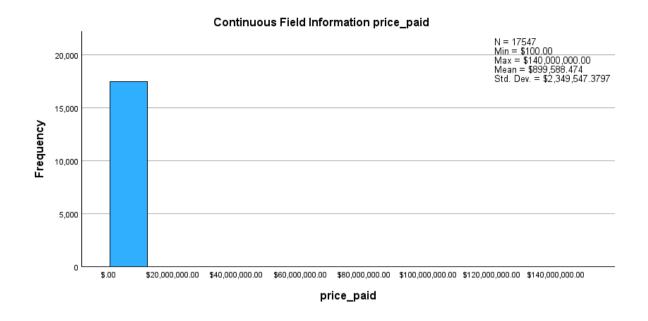
Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

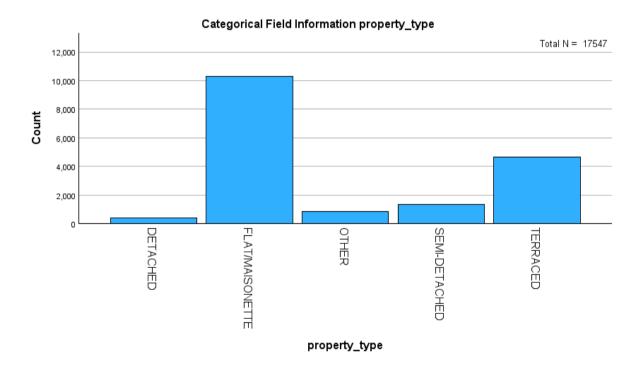
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

# Pairwise Comparisons of property\_type



Each node shows the sample average rank of property\_type.





So here also we'll reject the null hypothesis.

Null Hypothesis (H0):

The type of property in London has no discernible impact on the selling price.

H0:  $\mu$ \_apartment =  $\mu$ \_house, symbolically

Alternate hypothesis (Ha):

The type of property in London has a substantial impact on the selling price.

Ha:  $\mu$ \_apartment  $\neq \mu$ \_house, symbolically

Now for 3rd Research Question:

Does the kind of estate—freehold or leasehold—have a big influence on how much a London property sells for?

For this first converted the variable estate\_type which was string having the FREEHOLD and LEASEHOLD, so converting them to binary i.e

LEASEHOLD changed to 1 and FREEHOLD changed to 2.

This is done by by clicking on Transform-> Recode into Different Variables.

And then selecting the estate\_type form list of variables on the left and moved it to the Input variable box on the right.

And then in the Output variable entered the new variable name i.e estate\_type\_code.

And then clicked on the change button.

Enter the value you wish to replace for each entry in the "Old Value" field.

Set the previous leasehold value to the appropriate amount (for example, 1).

Change the previous freehold value to the other matching value (for example, 2).

And finally got the variable, as can be seen below

10	& estate_type_code
	1.00
	1.00
	1.00
	1.00
	1.00
	1.00
	1.00
	1.00
	1.00
	1.00
	1.00
	1.00
	2.00
	2.00
	1.00
	1.00
	1.00
	1.00
	1.00

So now,

Depending on how your data is distributed, you may use a t-test or a Mann-Whitney U test to determine if the kind of estate (freehold or leasehold) has a substantial influence on the selling price of houses in SPSS.

Go to "Compare Means" > "Analyse" > "Independent Samples T-Test":

Navigate to Analyse from the menu bar, then choose Compare Means, and lastly, Independent Samples T-Test.

Choose Your Variables:

In the dialogue box for the Independent Samples T-Test:

Place the variable (such as price\_paid) that represents the selling price in the "Test Variable(s)" box.

Place the estate type variable (such as estate\_type) in the "Grouping Variable" box. Describe Groups:

To designate the test groups, click the "Define Groups" option.

In "Group 1," type the freehold-corresponding value.

Enter the value that corresponds to leasehold for "Group 2".

Choices (if required):

Depending on your data's properties, you can investigate other choices, such correcting for uneven variances.

To run the analysis, click "OK":

### T-Test

# **Group Statistics**

	estate_type_code	N	Mean	Std. Deviation	Std. Error Mean
price_paid	2.00	6678	1300835.3327	3403862.6052	\$41,653.24246
	1.00	10869	\$653,059.2140	1278453.6182	\$12,262.81516

			Ind	ependent	Samples	Test					
		Levene's Test to Variant					Hest	for Equality of Me	ans		
		F	Sio	1	a	1.1.	cance Two-Sided p	Mean Difference	Std. Error Difference	Bd% Confidenc Differ Lower	e Interval of the rence Upper
price_grand	Equal variances assumed	247.459	+.001	17,893	17545	< 001	001	647776.11873	\$36,203.74250	576813.19187	718719.04560
	Equal variances not assumed			14.919	7848.365	<.001	<.001	647776.11873	\$43,420.83882	562659.71196	732092:52550

# **Independent Samples Effect Sizes**

				95% Confidence Interval	
		Standardizer <sup>a</sup>	Point Estimate	Lower	Upper
price_paid	Cohen's d	2328466.6979	.278	.248	.309
	Hedges' correction	2328566.2393	.278	.248	.309
	Glass's delta	1278453.6182	.507	.475	.538

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

So here also rejecting the Null Hypothesis.

# Frequency Statistics:

#### Statistics

		estate_type	postcode	new_build	property_type
N	Valid	17547	17547	17547	17547
	Missing	0	0	0	0

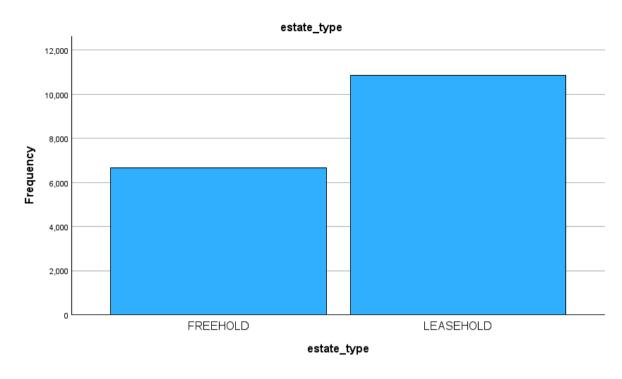
# estate\_type

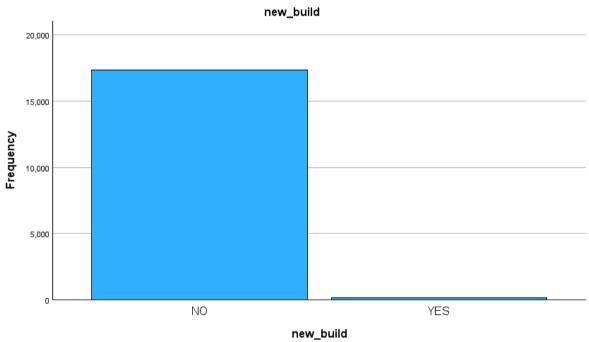
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	FREEHOLD	6678	38.1	38.1	38.1
	LEASEHOLD	10869	61.9	61.9	100.0
	Total	17547	100.0	100.0	

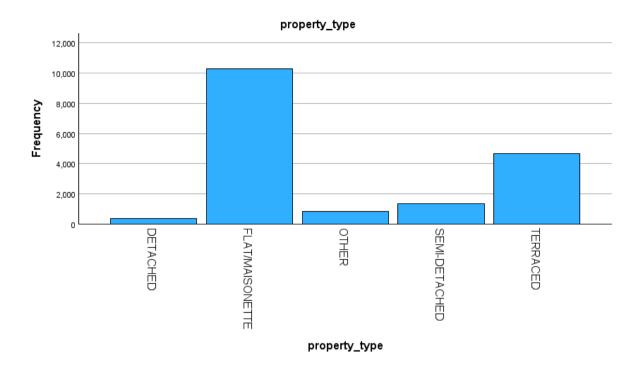
new_build								
		Frequency	Percent	Valid Percent	Cumulative Percent			
Valid	NO	17375	99.0	99.0	99.0			
	YES	172	1.0	1.0	100.0			
	Total	17547	100.0	100.0				

# property\_type

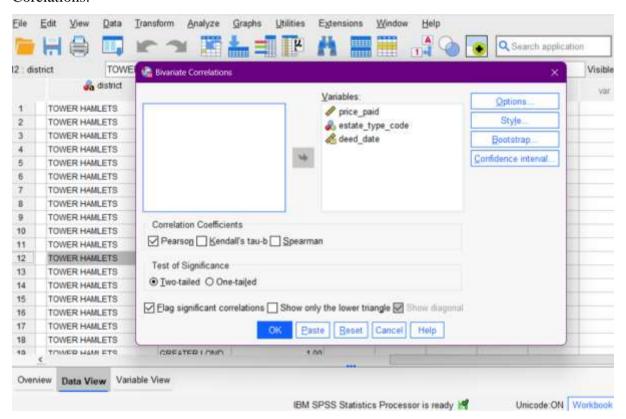
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	DETACHED	385	2.2	2.2	2.2
	FLAT/MAISONETTE	10298	58.7	58.7	60.9
	OTHER	861	4.9	4.9	65.8
	SEMI-DETACHED	1350	7.7	7.7	73.5
	TERRACED	4653	26.5	26.5	100.0
	Total	17547	100.0	100.0	







### Corelations:



# **Descriptive Statistics**

	Mean	Std. Deviation	N
price_paid	\$899,588.4738	2349547.3797	17547
estate_type_code	1.3806	.48554	17547
deed_date	03/29/23	53 16:56:34.7	17547

# Correlations

		price_paid	estate_type_co de	deed_date
price_paid	Pearson Correlation	1	.134**	.007
	Sig. (2-tailed)		<.001	.372
	N	17547	17547	17547
estate_type_code	Pearson Correlation	.134**	1	.032**
	Sig. (2-tailed)	<.001		<.001
	N	17547	17547	17547
deed_date	Pearson Correlation	.007	.032**	1
	Sig. (2-tailed)	.372	<.001	
	N	17547	17547	17547

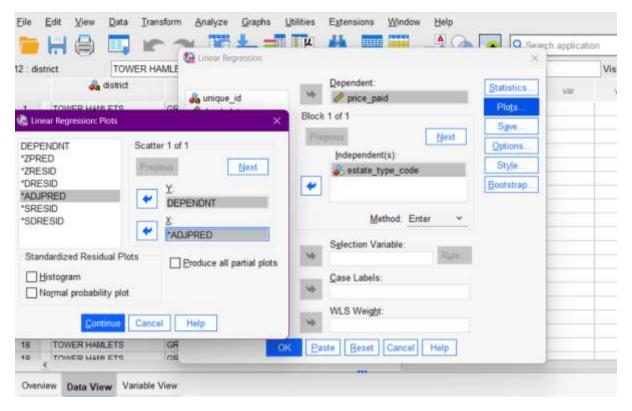
<sup>\*\*.</sup> Correlation is significant at the 0.01 level (2-tailed).

# **Regression Analysis:**

Does the type of estate (leasehold/freehold) impact housing prices?

Independent Variable: estate\_type

Dependent variable: price\_paid



# Variables Entered/Removeda

Model	Variables Entered	Variables Removed	Method
1	estate_type_co de <sup>b</sup>		Enter

- a. Dependent Variable: price\_paid
- b. All requested variables entered.

### Model Summary<sup>b</sup>

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.134ª	.018	.018	2328466.6979	.018	320.142	1	17545	<.001

- a. Predictors: (Constant), estate\_type\_code
- b. Dependent Variable: price\_paid

# Coefficients<sup>a</sup>

		Unstandardize	d Coefficients	Standardized Coefficients		
Model		В	Std. Error	Beta	t	Sig.
1	(Constant)	5283.095	52982.957		.100	.921
	estate_type_code	647776.119	36203.742	.134	17.893	<.001

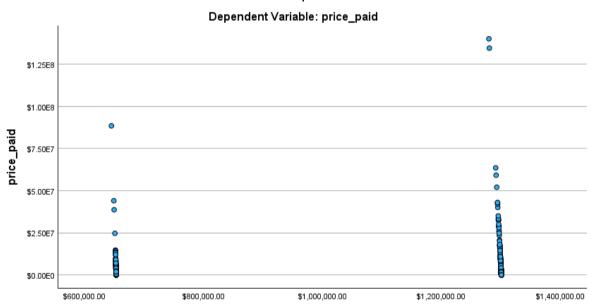
a. Dependent Variable: price\_paid

Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	\$653,059.1875	1300835.3750	\$899,588.4738	314523.01795	17547
Std. Predicted Value	784	1.276	.000	1.000	17547
Standard Error of Predicted Value	22334.449	28493.566	24678.473	2990.516	17547
Adjusted Predicted Value	\$644,985.3125	1301030.1250	\$899,588.4738	314523.18880	17547
Residual	-1300735.375	138699168.00	\$0.00000	2328400.3438	17547
Std. Residual	559	59.567	.000	1.000	17547
Stud. Residual	559	59.571	.000	1.000	17547
Deleted Residual	-1300930.125	138719936.00	\$0.00000	2328723.9525	17547
Stud. Deleted Residual	559	66.695	.001	1.053	17547
Mahal. Distance	.614	1.627	1.000	.492	17547
Cook's Distance	.000	.266	.000	.003	17547
Centered Leverage Value	.000	.000	.000	.000	17547

a. Dependent Variable: price\_paid

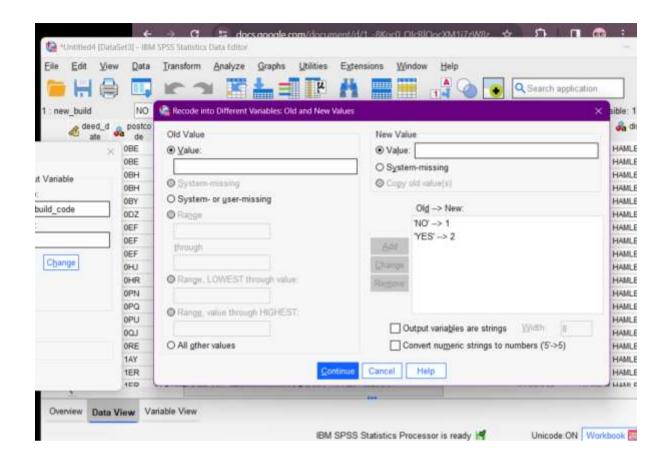




Regression Adjusted (Press) Predicted Value

How does the newness of a property (new build or not) relate to housing prices?

Independent Variable: new\_build Dependent variable: price\_paid



#### Variables Entered/Removeda

Model	Variables Entered	Variables Removed	Method
1	new_build_cod e <sup>b</sup>		Enter

- a. Dependent Variable: price\_paid
- b. All requested variables entered.

#### Model Summaryb

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.008ª	.000	.000	2349536.5690	.000	1.161	1	17545	.281

- a. Predictors: (Constant), new\_build\_code
- b. Dependent Variable: price\_paid

# **ANOVA**<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.412E+12	1	6.412E+12	1.161	.281 b
	Residual	9.685E+16	17545	5.520E+12		
	Total	9.686E+16	17546			

a. Dependent Variable: price\_paid

b. Predictors: (Constant), new\_build\_code

# Coefficients<sup>a</sup>

		Unstandardize	d Coefficients	Standardized Coefficients		
Model		В	Std. Error	Beta	t	Sig.
1	(Constant)	703660.336	182662.972		3.852	<.001
	new_build_code	194026.245	180035.031	.008	1.078	.281

a. Dependent Variable: price\_paid

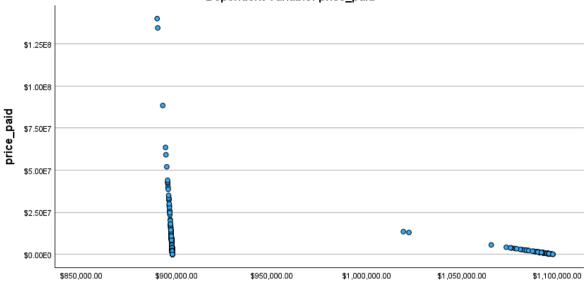
# Residuals Statisticsa

	Minimum	Maximum	Mean	Std. Deviation	Ν
Predicted Value	\$897,686.5625	1091712.8750	\$899,588.4738	\$19,115.98176	17547
Std. Predicted Value	099	10.050	.000	1.000	17547
Standard Error of Predicted Value	17824.600	179150.484	19405.956	15894.255	17547
Adjusted Predicted Value	\$889,680.2500	1097804.7500	\$899,588.4738	\$19,137.70602	17547
Residual	-1041712.812	139102320.00	\$0.00000	2349469.6144	17547
Std. Residual	443	59.204	.000	1.000	17547
Stud. Residual	445	59.206	.000	1.000	17547
Deleted Residual	-1047804.688	139110320.00	\$0.00000	2349663.5893	17547
Stud. Deleted Residual	445	66.184	.001	1.051	17547
Mahal. Distance	.010	101.012	1.000	9.951	17547
Cook's Distance	.000	.101	.000	.001	17547
Centered Leverage Value	.000	.006	.000	.001	17547

a. Dependent Variable: price\_paid

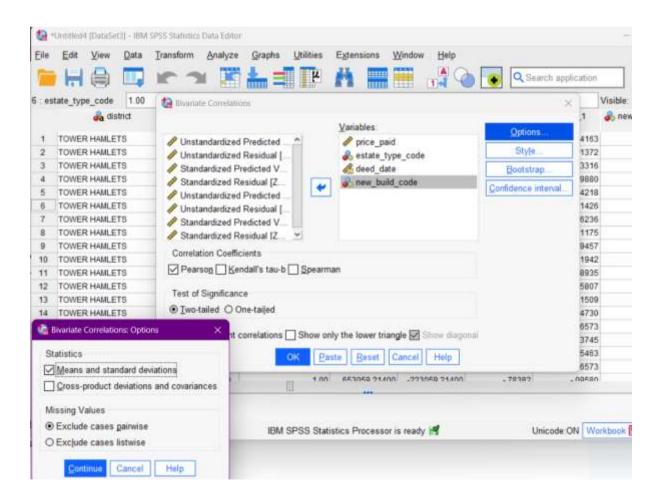
#### Scatterplot

#### Dependent Variable: price\_paid



Regression Adjusted (Press) Predicted Value

#### Correlation matrix:



# **Descriptive Statistics**

	Mean	Std. Deviation	N
price_paid	\$899,588.4738	2349547.3797	17547
estate_type_code	1.3806	.48554	17547
deed_date	03/29/23	53 16:56:34.7	17547
new_build_code	1.0098	.09852	17547

#### Correlations

		price_paid	estate_type_co de	deed_date	new_build_cod e
price_paid	Pearson Correlation	1	.134**	.007	.008
	Sig. (2-tailed)		<.001	.372	.281
	N	17547	17547	17547	17547
estate_type_code	Pearson Correlation	.134**	1	.032**	078**
	Sig. (2-tailed)	<.001		<.001	<.001
	N	17547	17547	17547	17547
deed_date	Pearson Correlation	.007	.032**	1	075**
	Sig. (2-tailed)	.372	<.001		<.001
	N	17547	17547	17547	17547
new_build_code	Pearson Correlation	.008	078**	075**	1
	Sig. (2-tailed)	.281	<.001	<.001	
	N	17547	17547	17547	17547

<sup>\*\*.</sup> Correlation is significant at the 0.01 level (2-tailed).

#### Task four: Evaluation and Conclusion

Regional Variations in the Cost of Homes:

Is there a significant difference in average housing prices between the boroughs of London? Conclusion: By using an ANOVA analysis, we were able to identify notable variations in the average cost of homes in each London borough. This implies that borough-to-borough housing values differ considerably.

# Property Type's Effect on Price:

Research Question: Does the kind of property (house, flat, etc.) have a statistically significant impact on the price of real estate in London?

In summary, we found that property type does affect price in a statistically significant way using ANOVA. The average selling price of various property kinds varies.

# Estate Type's Effect on Property Prices

Research Question: Is there a significant difference in the sale price of a London home

depending on whether the property is freehold or leasehold?

In summary: Using a t-test for independent samples, we discovered evidence that refuted the

null hypothesis. The selling prices of freehold and leasehold homes varies significantly.

Comprehensive Analysis of the Dataset:

Descriptive Statistics: For the key variables, descriptive statistics such as means median and

standard deviations were computed. It uncovered the facts of the variation and central

tendency of the dataset.

Data Cleaning and Preparation:

Data Transformation: Adequate preparation of the data was also ensured in this step by using

transformation and cleansing processes to ensure reliability and accuracy for later analysis.

Additional Understanding:

Correlation Matrix: The correlations among the variables were calculated by building a

correlation matrix. The diagram is used to determine the relationship between variables.

In the end, detailed interdependent patterns between variables that determine real estate price

emerged through housing data analysis in London. The results can help practitioners in the

real estate field as well as contribute to future research or decision making.

**Section 2: Data Modelling** 

**Entities and Attributes:** 

Task1: Design a relational Database

Customer

CustomerID (PK)

FirstName

LastName

**Email** 

Phone

Address

RegistrationDate

30

# LoyaltyPoints

# Product

ProductID (PK)

ProductName

Description

Price

StockQuantity

Weight

Dimensions

# Order

OrderID (PK)

OrderDate

ShippingAddress

PaymentMethod

OrderStatus

TotalAmount

**TaxAmount** 

ShippingFee

# OrderItem

OrderItemID (PK)

Quantity

Subtotal

# Vendor

VendorID (PK)

VendorName

ContactName

ContactEmail

Phone

Address

#### Review

ReviewID (PK)

Rating

ReviewText

ReviewDate

Relationships:

# Customer-Order Relationship:

A client can place a single order or several orders.

A client can have only one single order.

# Order-OrderItem Relationship:

Each order may contain one or more items from the list of orders.

Each order contains one item order.

# Product-OrderItem Relationship:

A product may be in any quantity or zero.

An order item is one product.

# Vendor-Product Relationship:

One vendor can offer one or several products.

A seller provides one product.

# Customer-Review Relationship:

This single consumer can write one review or several reviews.

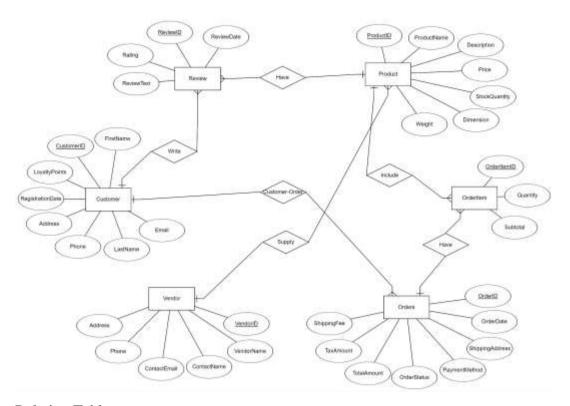
One customer writes one review.

# Product-Review Relationship:

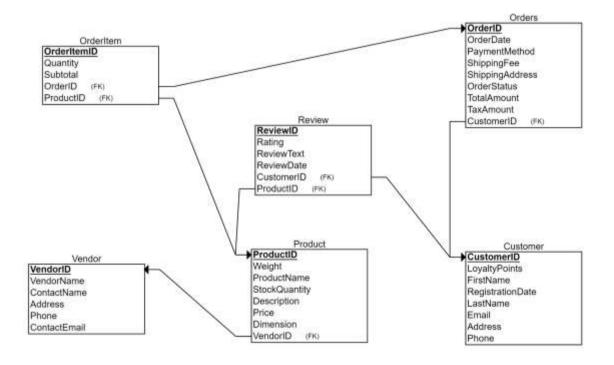
A product may have one review or many.

Every product gets one review.

**ERD** 



### **Relation Table**



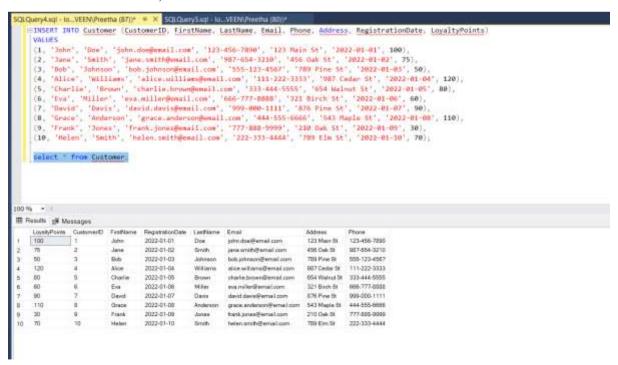
**Task 2: Write Code** 

INSERT INTO Customer (CustomerID, FirstName, LastName, Email, Phone, Address, RegistrationDate, LoyaltyPoints)

#### **VALUES**

- (1, 'John', 'Doe', 'john.doe@email.com', '123-456-7890', '123 Main St', '2022-01-01', 100),
- (2, 'Jane', 'Smith', 'jane.smith@email.com', '987-654-3210', '456 Oak St', '2022-01-02', 75),
- (3, 'Bob', 'Johnson', 'bob.johnson@email.com', '555-123-4567', '789 Pine St', '2022-01-03', 50),
- (4, 'Alice', 'Williams', 'alice.williams@email.com', '111-222-3333', '987 Cedar St', '2022-01-04', 120),
- (5, 'Charlie', 'Brown', 'charlie.brown@email.com', '333-444-5555', '654 Walnut St', '2022-01-05', 80),
- (6, 'Eva', 'Miller', 'eva.miller@email.com', '666-777-8888', '321 Birch St', '2022-01-06', 60),
- (7, 'David', 'Davis', 'david.davis@email.com', '999-000-1111', '876 Pine St', '2022-01-07', 90),
- (8, 'Grace', 'Anderson', 'grace.anderson@email.com', '444-555-6666', '543 Maple St', '2022-01-08', 110),
- (9, 'Frank', 'Jones', 'frank.jones@email.com', '777-888-9999', '210 Oak St', '2022-01-09', 30), (10, 'Helen', 'Smith', 'helen.smith@email.com', '222-333-4444', '789 Elm St', '2022-01-10', 70);

#### select \* from Customer;



INSERT INTO OrderS (OrderID, OrderDate, ShippingAddress, PaymentMethod, OrderStatus, TotalAmount, TaxAmount, ShippingFee, CustomerID)

#### **VALUES**

- (1, '2022-01-15', '123 Main St', 'Credit Card', 'Shipped', 150.00, 15.00, 10.00, 3),
- (2, '2022-01-16', '456 Oak St', 'PayPal', 'Processing', 200.00, 20.00, 15.00, 7),
- (3, '2022-01-17', '789 Pine St', 'Credit Card', 'Delivered', 100.00, 10.00, 8.00, 5),
- (4, '2022-01-18', '987 Cedar St', 'Cash on Delivery', 'Shipped', 120.00, 12.00, 5.00, 1),
- (5, '2022-01-19', '654 Walnut St', 'Credit Card', 'Processing', 180.00, 18.00, 12.00, 10),
- (6, '2022-01-20', '321 Birch St', 'PayPal', 'Delivered', 90.00, 9.00, 7.00, 2),
- (7, '2022-01-21', '876 Pine St', 'Credit Card', 'Shipped', 130.00, 13.00, 9.00, 6),
- (8, '2022-01-22', '543 Maple St', 'Cash on Delivery', 'Processing', 160.00, 16.00, 11.00, 4),
- (9, '2022-01-23', '210 Oak St', 'PayPal', 'Delivered', 110.00, 11.00, 6.00, 8),
- (10, '2022-01-24', '789 Elm St', 'Credit Card', 'Shipped', 140.00, 14.00, 8.00, 9);

### select \* from Orders;

```
| THERE INTO Order 5 (Order ID, OrderDate, Shipping&ddress, PaymentMethod, OrderStatus, TotalAssount, TaxAssount, ShippingFae, CustimenFID)
| VAUUS | (1, '2822-01-15', '125 Main 5t', 'Credit Card', 'Shipped', 150.00, 15.00, 1), (2, '2822-01-16', '455 Oak St', 'SoyPal', 'Potensing', 200.00, 20.00, 15.00, 7), (3, '2822-01-16', '455 Oak St', 'SoyPal', 'Potensing', 100.00, 10.00, 00.00, 10.00, 5), (4, '2022-01-18', '937 Cedar St', 'Credit Card', 'Believend', 180.00, 11.00, 5.00, 11, (5, '2022-01-18', '937 Cedar St', 'Credit Card', 'Potensing', 180.00, 11.00, 5.00, 11, (6, '2022-01-20', '221 Nirth St', 'Potensing', 'Potensing', 180.00, 11.00, 12.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00, 10.00,
```

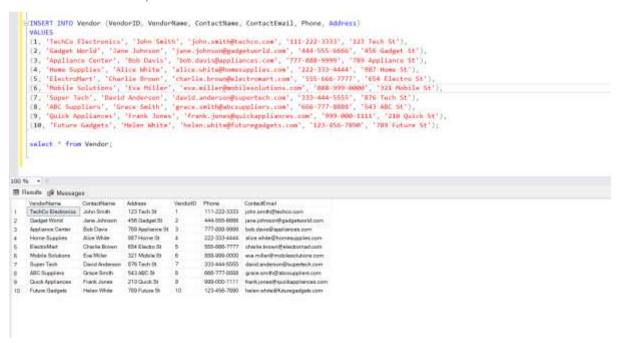
INSERT INTO Vendor (VendorID, VendorName, ContactName, ContactEmail, Phone, Address)

### **VALUES**

- (1, 'TechCo Electronics', 'John Smith', 'john.smith@techco.com', '111-222-3333', '123 Tech St'),
- (2, 'Gadget World', 'Jane Johnson', 'jane.johnson@gadgetworld.com', '444-555-6666', '456 Gadget St'),
- (3, 'Appliance Center', 'Bob Davis', 'bob.davis@appliances.com', '777-888-9999', '789 Appliance St'),

- (4, 'Home Supplies', 'Alice White', 'alice.white@homesupplies.com', '222-333-4444', '987 Home St'),
- (5, 'ElectroMart', 'Charlie Brown', 'charlie.brown@electromart.com', '555-666-7777', '654 Electro St'),
- (6, 'Mobile Solutions', 'Eva Miller', 'eva.miller@mobilesolutions.com', '888-999-0000', '321 Mobile St'),
- (7, 'Super Tech', 'David Anderson', 'david.anderson@supertech.com', '333-444-5555', '876 Tech St'),
- (8, 'ABC Suppliers', 'Grace Smith', 'grace.smith@abcsuppliers.com', '666-777-8888', '543 ABC St'),
- (9, 'Quick Appliances', 'Frank Jones', 'frank.jones@quickappliances.com', '999-000-1111', '210 Quick St'),
- (10, 'Future Gadgets', 'Helen White', 'helen.white@futuregadgets.com', '123-456-7890', '789 Future St');

#### select \* from Vendor;



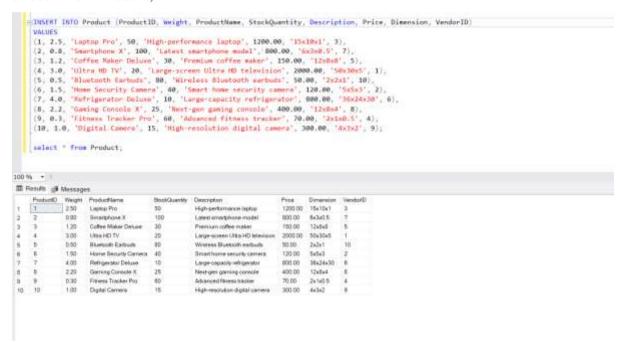
INSERT INTO Product (ProductID, Weight, ProductName, StockQuantity, Description, Price, Dimension, VendorID)

#### **VALUES**

- (1, 2.5, 'Laptop Pro', 50, 'High-performance laptop', 1200.00, '15x10x1', 3),
- (2, 0.8, 'Smartphone X', 100, 'Latest smartphone model', 800.00, '6x3x0.5', 7),

- (3, 1.2, 'Coffee Maker Deluxe', 30, 'Premium coffee maker', 150.00, '12x8x8', 5),
- (4, 3.0, 'Ultra HD TV', 20, 'Large-screen Ultra HD television', 2000.00, '50x30x5', 1),
- (5, 0.5, 'Bluetooth Earbuds', 80, 'Wireless Bluetooth earbuds', 50.00, '2x2x1', 10),
- (6, 1.5, 'Home Security Camera', 40, 'Smart home security camera', 120.00, '5x5x3', 2),
- (7, 4.0, 'Refrigerator Deluxe', 10, 'Large-capacity refrigerator', 800.00, '36x24x30', 6),
- (8, 2.2, 'Gaming Console X', 25, 'Next-gen gaming console', 400.00, '12x8x4', 8),
- (9, 0.3, 'Fitness Tracker Pro', 60, 'Advanced fitness tracker', 70.00, '2x1x0.5', 4),
- (10, 1.0, 'Digital Camera', 15, 'High-resolution digital camera', 300.00, '4x3x2', 9);

#### select \* from Product;



INSERT INTO Review (ReviewID, Rating, ReviewText, ReviewDate, CustomerID,

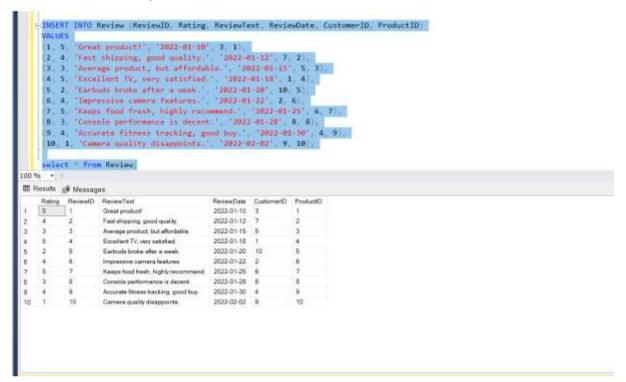
# ProductID)

### **VALUES**

- (1, 5, 'Great product!', '2022-01-10', 3, 1),
- (2, 4, 'Fast shipping, good quality.', '2022-01-12', 7, 2),
- (3, 3, 'Average product, but affordable.', '2022-01-15', 5, 3),
- (4, 5, 'Excellent TV, very satisfied.', '2022-01-18', 1, 4),
- (5, 2, 'Earbuds broke after a week.', '2022-01-20', 10, 5),
- (6, 4, 'Impressive camera features.', '2022-01-22', 2, 6),
- (7, 5, 'Keeps food fresh, highly recommend.', '2022-01-25', 6, 7),
- (8, 3, 'Console performance is decent.', '2022-01-28', 8, 8),

- (9, 4, 'Accurate fitness tracking, good buy.', '2022-01-30', 4, 9),
- (10, 1, 'Camera quality disappoints.', '2022-02-02', 9, 10);

# select \* from Review;



# INSERT INTO OrderItem (OrderItemID, Quantity, Subtotal, OrderID, ProductID)

#### **VALUES**

- (1, 2, 2400.00, 1, 5),
- (2, 3, 2400.00, 2, 8),
- (3, 1, 150.00, 3, 3),
- (4, 2, 4000.00, 4, 7),
- (5, 5, 250.00, 5, 2),
- (6, 1, 120.00, 6, 10),
- (7, 2, 2600.00, 7, 1),
- (8, 1, 400.00, 8, 9),
- (9, 3, 210.00, 9, 6),
- (10, 1, 300.00, 10, 4);

select \* from OrderItem;

# **Task 3: Explanations with Queries**

1. Retrieve Products and Their Average Rating

**SELECT** 

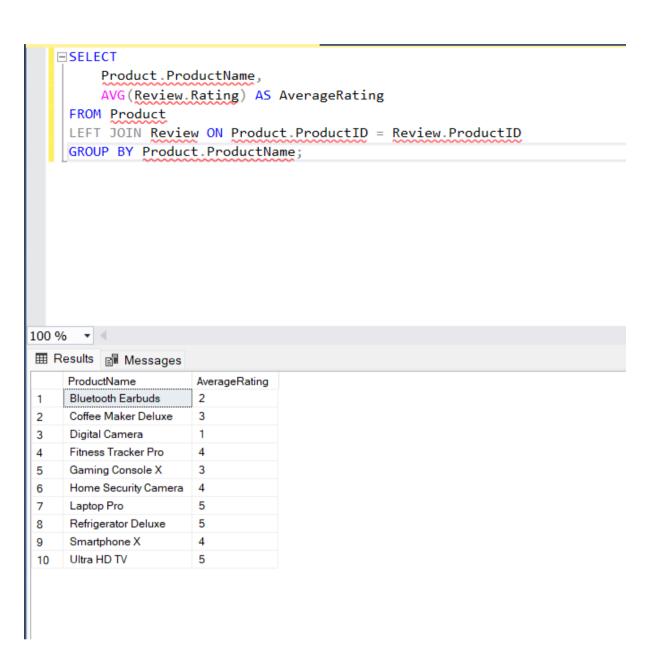
Product.ProductName,

AVG(Review.Rating) AS AverageRating

FROM Product

LEFT JOIN Review ON Product.ProductID = Review.ProductID

GROUP BY Product.ProductName;



2. Find Customers with the Highest LoyaltyPoints

**SELECT TOP 3** 

CustomerID,

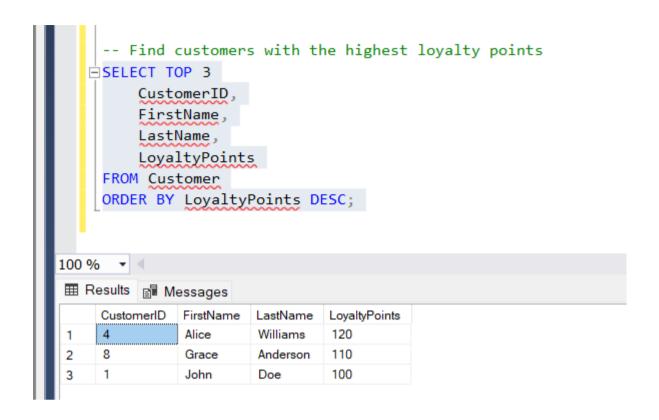
FirstName,

LastName,

LoyaltyPoints

FROM Customer

ORDER BY LoyaltyPoints DESC;



# 3. Identify top 5 Best-Selling Products

**SELECT TOP 5** 

Product.ProductID,

Product.ProductName,

SUM(OrderItem.Quantity) AS TotalQuantitySold

FROM Product

JOIN OrderItem ON Product.ProductID = OrderItem.ProductID

GROUP BY Product.ProductID, Product.ProductName

ORDER BY TotalQuantitySold DESC;

```
-- Identify best-selling products
   SELECT TOP 5
        Product.ProductID,
        Product ProductName.
         SUM(OrderItem.Quantity) AS TotalQuantitySold
    FROM Product
    JOIN OrderItem ON Product.ProductID = OrderItem.ProductID
    GROUP BY Product.ProductID, Product.ProductName
    ORDER BY TotalQuantitySold DESC;
    -- Calculate revenue by vendor
.00 % ▼ ∢
ProductID
            ProductName
                             TotalQuantitySold
    2
             Smartphone X
    6
             Home Security Camera
                             3
2
    8
             Gaming Console X
                              3
3
    1
             Laptop Pro
                              2
4
    5
             Bluetooth Earbuds
                              2
```

# 4. Calculate Revenue by Vendor

**SELECT** 

Vendor.VendorID,

Vendor.VendorName,

SUM(OrderItem.Subtotal) AS TotalRevenue

FROM Vendor

JOIN Product ON Vendor.VendorID = Product.VendorID

JOIN OrderItem ON Product.ProductID = OrderItem.ProductID

GROUP BY Vendor. VendorID, Vendor. VendorName

ORDER BY TotalRevenue DESC:

```
-- Calculate revenue by vendor
   SELECT
          Vendor.VendorID,
          Vendor.VendorName,
          SUM(OrderItem.Subtotal) AS TotalRevenue
     FROM Vendor
     JOIN Product ON Vendor.VendorID = Product.VendorID
     JOIN OrderItem ON Product.ProductID = OrderItem.ProductID
     GROUP BY Vendor.VendorID, Vendor.VendorName
     ORDER BY TotalRevenue DESC;
100 %
      - ▼ - 4
VendorID
              VendorName
                              TotalRevenue
     6
              Mobile Solutions
                              4000.00
     3
              Appliance Center
                              2600.00
 2
     8
 3
              ABC Suppliers
                              2400.00
     10
              Future Gadgets
                              2400.00
 4
5
     4
              Home Supplies
                              400.00
6
     1
              TechCo Electronics
                              300.00
 7
     7
              Super Tech
                              250.00
8
     2
              Gadget World
                              210.00
     5
9
              ElectroMart
                              150.00
     9
 10
              Quick Appliances
                              120.00
```

#### 5. Retrieve Customer Reviews

### **SELECT**

Review.ReviewID,

Review.Rating,

Review.ReviewText,

Review.ReviewDate,

Customer.FirstName,

Customer.LastName,

Product.ProductName

#### FROM Review

JOIN Customer ON Review.CustomerID = Customer.CustomerID

JOIN Product ON Review.ProductID = Product.ProductID

WHERE Product.ProductName = 'Smartphone X';

