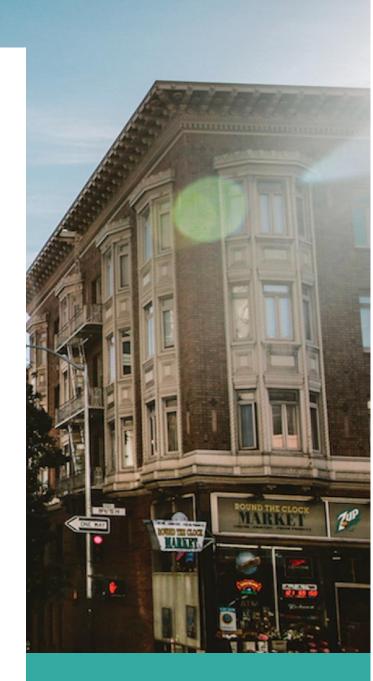
Houses for rent in Madrid

Global Master in Big Data & Business Analytics

Machine Learning I

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TEAM A

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Introduction

The purpose of this executive summary is to explain the model used to **estimate house rental prices** based on a set of explanatory variables related with their characteristics. The dataset used has more than 2000 houses that are available for rent in Madrid. Team A followed the following **machine learning process** to build a Linear Regression Model:

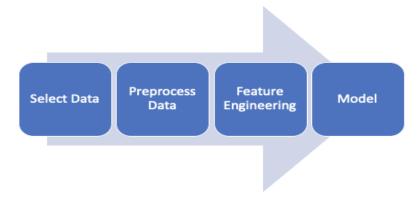


Illustration: Process of Machine Learning

Key Findings

• The model allows users to estimate rental prices of properties not included in the dataset yet have similar characteristics as those houses in the dataset

Pre-processing

After selecting the data, Team A completed data pre-processing, which includes checking for missing values, checking for categorical variables, and feature scaling. Out of 15 features, there are 6 features that have missing values: Number, Area, Bedrooms, Outer, and Elevator. For the **numerical features** that are missing values, such as Bedrooms, **missing values were imputed with the average of values**. Similar to ID and Address, since Number does not provide any added value, Team A considered it irrelevant for the analysis and thus, excluded the feature model. For the **categorical features** that are missing values, such as Area, Outer, Floor, and Elevator, **missing values were imputed with the most frequent values** and handled using **dummy encoding**. In regard to feature scaling, Team A decided to apply standard rescaling to numerical features.



Feature engineering

Although there were originally 14 explanatory variables, Team A decided to only use 10 explanatory variables. The variables Team A excluded are Address, Number, District, and ID (Rent is the dependent variable, meaning that it was excluded as an explanatory variable by default). Team A also did not create additional variables. Here is an illustration of the explanatory variables in the model:

Input features						
Floor	-	"A" Category	Dummy-encode, impute missing			
Penthouse		"A" Category	Dummy-encode, impute missing			
Outer		"A" Category	Dummy-encode, impute missing			
Semidetached		"A" Category	Dummy-encode, impute missing			
Duplex		"A" Category	Dummy-encode, impute missing			
Area	Input	"A" Category	Dummy-encode, impute missing			
Sq. Mt		# Numeric	Avg-std rescaling			
Bedrooms		# Numeric	Avg-std rescaling			
Elevator		"A" Category	Dummy-encode, impute missing			
Cottage		"A" Category	Dummy-encode, impute missing			
District		"A" Category	Dummy-encode, impute missing			
Rent	Target	# Numeric				

Table: Input features

In an effort to **prevent collinearity**, or a condition in which some of the independent variables are highly correlated, Team A decided **to exclude one of the geographic variables: District**. Team A decided to exclude District over Area given that the later is a more granular explanatory variable, representing a smaller geographic region in Madrid than Area.

Model

The algorithm used to build a linear regression model in Dataiku Data Science Studio (DSS) was the **Ordinary Least Squares (OLS) regression algorithm**. Given that the goal is to explain house rental prices, the target of this model is the variable Rent. The train-test ratio is 80-20, which is the default option in DSS. Roughly 1748 rows were used as the training set and 440 rows were used for the test set. The method of **optimization is based on the R2** since it tends to be the most prominent evaluator for linear regression models.

Coefficients

In linear regression, coefficients are the values per explanatory variable that change the dependent variable. For example, per the following illustration, if a house in Madrid does not have a



Penthouse (a binary explanatory variable), the rental price decreases by roughly 273 Euros. Adversely, a house in the Area of Jerónimos, the rental price increases by roughly 1624 Euros.

Regression coefficients					
Variable	Coefficient				
Area is Jerónimos	1,624				
Area is Recoletos	1,416				
Area is El Viso	1287				
Area is Nino Jesus	1020				
Area is Castellana	1019				
Area is El Viso	964				
Area is Almagro	921				

Table: Sample of Regression Coefficients

Evaluation Metrics

Given that Team A built a linear **regression model**, there are several evaluation metrics to consider, such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R²; however, the metrics Team A **decided to optimize the hyperparameters for was R2**. The following illustration details the evaluation metrics of the linear regression model:

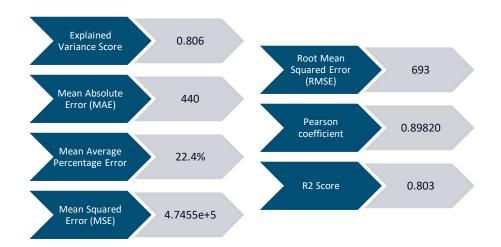


Illustration: Detailed Metrics



MAE, MSE, & R2

The MAE is the difference between the predicted values and observed values, or the "error" between the predicted values and the observed values. A MAE of 440 is reasonably good knowing that lower MAE values are better. Previously run models with less significant variables yielded a greater MAE than 440. The MSE is the summation of the square of distance between predicted values and observed values. An MSE of 4.7455e+5 is fairly good knowing that the lower MSE values are better. Previously run models with less significant variables yielded a greater MSE than 47455e+5. The R2 explains how well the explanatory variables explain the variability in the dependent model. An R2 of roughly 80% is satisfactorily good knowing that R2 scores closer to 1 are better.

Conclusions

Given that the explanatory variables explain roughly 80% of the variability in the dependent variable, Team A has a good OLS model. As a result, the value add of this model is twofold:

The model allows for the **comparison**of rental prices of properties with
similar characteristics in different

The model helps identify the **most and the least expensive districts** in Madrid and recognize the **key features** that affects the variability of the house rentals in Madrid

For example, a house in Madrid, particularly in the Area of Colina, might have the following characteristics:

Area	Bedrooms	Sq. Mt	Floor	Outer	Elevator	Penthouse	Cottage	Duplex	Semi Detached
Colina	2	90-110	3	Yes	Yes	No	No	No	No

Table: House Characteristics Example

The model has predicted the rental price of houses with similar characteristics in the area of Colina at roughly 1,290 Euros. This means that rental properties in Colina with similar characteristics have an estimated rental price of 1,290 Euros. Unfortunately, there will be instances in which the predicted value is greater than the actual value; however, the OLS modelling method is one of the best possible options to determine an estimated rental price. Furthermore, the model yields a comparison of estimated rental prices of properties in different Areas, as shown in the Tableau Dashboard Team A created called Madrid's Houses Rentals. If a potential tenant wanted a rental property with the aforementioned characteristics but had a specific willingness to pay (WTP), this model could help them evaluate their options based on their WTP.



Technical Annex

Data Dictionary

Field Name	Data Type	ta Type Data Field Size Description		Description	Example
ID	Integer			Identifier	3
District	Text			District in	Ciudad
				Madrid	Lineal
Address	Text			Address in	Piso en
				Madrid	calle de
					Vicente
					Muzas
Number	Integer			House #	4
Area	Text			Area in	Colina
				Madrid	
Rent	Integer			Monthly rent	1300
Bedrooms	Integer			# of	2
				bedrooms	
Sq.Mt	Integer			Square	100
				meters	
Floor	Integer			# of floors	3
Outer	Integer			Has outer	1
				space	
Elevator	Integer			Has elevator	1
Penthouse	Integer			Has	0
				penthouse	
Cottage	Integer			Has cottage	0
Duplex	Integer			Is a duplex	0
Semidetached	Integer			Is	0
				semidetached	



Regression Summary Table

The regression summary table provides a valuable insight into the model, including: **Coefficient, Standard Error and P Value (Significant level)**.

Out[19]: OLS Regression Results

OLS Regression Resu	IIIS								
Dep. Variable:	у	R	-squared:	0.801					
Model:	OLS	Adj. R	-squared:	0.788					
Method:	Least Squares	F	-statistic:	59.79					
Date:	Thu, 09 Jul 2020	Prob (F-	statistic):	0.00					
Time:	08:06:05	Log-Li	kelihood:	-17378.					
No. Observations:	2188		AIC:	3.503e+04					
Df Residuals:	2049		BIC:	3.582e+04					
Df Model:	138								
Covariance Type:	nonrobust								
			coef	std err	t	P> t	[0.025	0.975]	
		const	415.2375	141.320	2.938	0.003	138.091	692.384	
	Ве	drooms	80.4286	24.362	3.301	0.001	32.652	128.205	
		Sq.Mt	1264.2635	30.704	41.176	0.000	1204.049	1324.478	
	Penthouse_	value_0	91.5887	75.478	1.213	0.225	-56.432	239.609	
	Penthouse_	value_1	323.6487	79.783	4.057	0.000	167.185	480.113	
	Semidetached_	value_0	287.9235	103.568	2.780	0.005	84.814	491.033	
	Semidetached_	value_1	127.3140	113.397	1.123	0.262	-95.072	349.700	

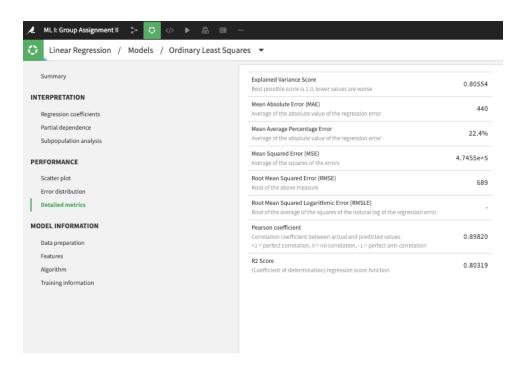
Table: Regression Summary

^{*}We have exported our model into python to get the regression summary table, please find attached python file for full view of the summary table.

^{**}We acknowledge the values from the summary table are very close to what DSS UI highlights, however, they are not 100% exact.



Detailed Metrics

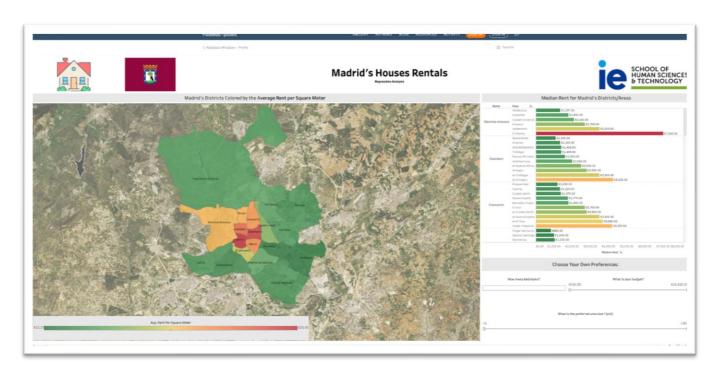




Test Data with Predictions



Madrid's House Rentals



(click on illustration to visit Tableau Dashboard)