

UNIVERSITAT AUTÒNOMA DE BARCELONA

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# APPLIED MACHINE LEARNING: ANALYSIS AND IMPLEMENTATION

RESEARCH INNOVATION (PYTHON REPORT)

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## **Abstract**

In a world of growing volumes and varieties of data, coding manually can become a problem to achieve relevant insight and knowledge. Using machine learning, we are able develop a solution by understanding the construction of algorithms and applications in the right scope of data sources. And based on the awareness of improvement of computer programs, we can now access data, analyze it and learn from it.

The focus will be to study supervised machine learning algorithms on the process of predicting a continuous variable through machine learning techniques.

An official dataset will be used with python libraries and original implementations will be developed using regression algorithms and models. More specifically, prediction of house prices based on single and multiple features will be conducted.

The regression analysis, study and implementation were explained using selected supervised machine learning algorithmic models. Results of applied machine learning discovered were also deliberated.

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# 1 Introduction

SINCE the dawn of time, computers were known as a machine used to input data and process it to generate a relevant output. Today, they have made human life stress-free and over time have developed into the key solution to all daily computational tasks. Over the last decade, these computational tasks begin to establish a steadily increasing in the amounts of data that became available for all kinds of business needs. This kind of data growth reduces the amount of knowledge that we need to achieve today's normal relevant objectives.

It is widely known, that what we lack in knowledge, we make up for in data. This is where we can establish a form of learning, not only for technical valuation and data recovery, but a combination of two capabilities of a computer system to make it perform learning task and make coherent results according to previously observed conditions and previous actions or responses, and not only act according to an immovable strategy. We call this "Machine learning". A kind of Learning that is imperatively needed when the task to be executed by the computer system or machine is too complicate to be explained in code or within any unknown conditional data mapping.

Within the realm of machine learning, it is very imperative when the task to be executed by the computer system is too complicate a relevant type of machine learning algorithm must be selected.

## 2 Definitions & Concepts

To conduct our study of applied machine learning, it is important to declare all essential definitions and concepts.

Generally, there are three types of machine Learning algorithms: Supervised Learning, Unsupervised Learning and Reinforcement Learning. We are using Supervised Learning for this project

**Supervised Learning** is a type of machine learning algorithm that consists of a dependent variable which is to be predicted from a given set of independent variables. Within this set of independent variables, a function must be generated to map inputs to the desired output. This in theory is called “training process”. This process continues until the model achieves a successful level of accuracy on the training data. Illustrations of this type of learning algorithm are Regression, Decision Tree, Random Forest, KNN, Logistic Regression etc.

## 3 Objectives

Our focus will be to study supervised machine learning algorithms on the process of predicting a continuous variable through machine learning techniques. More specifically, we want to predict house prices based on single and multiple features using regression analysis.

We will use the dataset from house sales in King County in Seattle, USA, with programming libraries and implementations will be developed using regression algorithms and models.

In this report, we will first apply some data analysis techniques to summarize the main characteristics of the dataset. Then we will apply various machine learning algorithms, change some of the tuning parameters to see if we can make an improvement of the code.

## 4 Algorithmic Methods & Models

Regression analysis provides a "best-fit" mathematical equation for the value of variables. The equation may be linear (a straight line) or polynomial.

The data set is splitted on just two types of features, "y" and "x". They are called the dependent variable (y) and independent variable (x), the purpose of this type of analysis is to estimate or predict what "y" will be a given value or values of "x".

We will use the following six (6) methods and/or models:

- **Simple Regression**
- **Multiple (Polynomial) Regression**
- **Ridge Regression and Gradient Descent**
- **Lasso and Coordinate Descent**
- **K-Nearest Neighbors**

We will now define our selected supervised machine learning algorithmic models.

### 4.1 Linear Regression

The simple regression model is a linear equation having a y-intercept and a slope with approximations of these population parameters based on sample data and determined by standard formulas.

The formula for the simple regression model is:

$$y_j = \beta_o + \beta_1 x_i + \varepsilon_i \quad (1)$$

where

$y_j$  = a value of the dependent variable,  $y$ ,

$x_i$  = a value of the independent variable,  $x$ ,

$\beta_o$  = the y-intercept of the regression line,

$\beta_1$  = the slope of the regression line and

$\varepsilon_i$  = random error, or residual

### 4.2 Multiple (Polynomial) Regression

The multiple regression model is an extension of the simple linear regression model. However, there are two or more independent variables instead of just one. It is sometimes called "*polynomial regression model*". As before, estimates of the population parameters in the model are made on the basis of sample data.

The formula for the multiple regression model is:

$$y_j = \beta_o + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki} + \varepsilon_i \quad (2)$$

where

$x_{1i} + x_{2i} + \dots + \beta_k x_{ki}$  = a value of the independent variable,  $x$ ,

$x_{1i} + x_{2i} + \dots + x_{ki}$  = the slope of the regression line,

$\beta_1 + \beta_2 + \dots + \beta_k$  = partial regression coefficients for the independent variables,  $x_{1i} + x_{2i} + \dots + x_{ki}$  and

## 4.3 Ridge Regression and Gradient Descent

### 4.3.1 Ridge Regression

Ridge regression is type of shrinkage methods used to construct simple models with excessive descriptive extrapolative power. Such simple models explain data with minimum number of parameters or predictor variables. Within the process of ridge regression, it is normally used to create these simple model when the data set has multicollinearity or correlation exist between predictor variables.

The formula used for the ridge regression is:

$$\sum_{i=1}^n \left( y_i - \beta_0 + \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p \beta_j^2 = RSS + \lambda \sum_{j=1}^p \beta_j^2 \quad (3)$$

where

$RSS$  = Residual Sum Of Squares, which is a statistical procedure used to quantify the volume of variance in a data set that is not described by a regression model and

$\lambda \sum_{j=1}^p \beta_j^2$  = the shrinkage penalty with  $\lambda \geq 0$  as a tuning parameter.

### 4.3.2 Gradient Descent

Gradient descent is used to minimize some function by iteratively moving in the direction of steepest descent as defined by the negative of the gradient. Gradient descent is to update the parameters of our model.

The gradient is the direction of increase and therefore the negative gradient is the direction of decrease and we're trying to minimum the number of parameters or predictor variables.

The move in the negative gradient direction is called the '*step size*'.

## 4.4 Lasso and Coordinate Descent

### 4.4.1 Lasso

When using the ridge regression, there exist some disadvantages located in the penalty (3). The idea of the shrinking process is to shrink all coefficients to zero however, not all will be set to exactly zero. This will only happen when  $\lambda = \infty$ . This leads to the need of the *Lasso*, which is an alternative version to ridge regression that is used to correct this disadvantage.

The formula used for the lasso is:

$$\sum_{i=1}^n \left( y_i - \beta_0 + \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p |\beta_j| = RSS + \lambda \sum_{j=1}^p |\beta_j| \quad (4)$$

where

$RSS$  = Residual Sum Of Squares, which is a statistical procedure used to quantify the volume of variance in a data set that is not described by a regression model and

$\lambda \sum_{j=1}^p |\beta_j|$  = the lasso penalty with  $\lambda \geq 0$  as a tuning parameter.

In (3), the  $\beta_j^2$  term in the ridge regression penalty changes to  $|\beta_j|$  lasso penalty term to correct the disadvantage in the ridge regression.

## 4.5 K-Nearest Neighbors

k-nearest neighbors or k-NN is an algorithm that classifies an input by using its k nearest neighbors.

k-NN is known as data classification and regression algorithm that tries to govern what collection of data points its in by looking at the data points surrounding it.

Since our focus is on the regression case, in k-NN regression, the output is the property amount for the item. This amount is the mean of the values of its k nearest neighbors.

The k-NN regression method is closely related to the k-NN classifier method and using the formula:

$$\hat{f}(x_o) = \frac{1}{K} \sum_{x_i \in G_o} \quad (5)$$

where

$x_o$  = a prediction point,

$K$  = given value or amount,

$G_o$  = a group of training responses and

$x_i$  = a trained response



## 5 Data Overview

As discussed earlier, we use a dataset for the sales coming from an approved public records of home sales in the King County Area, Washington State, USA.

The data set comprises of 21,613 rows.

Each characterizes of a home sold from May 2014 through May 2015.

Below is a breakdown of the variables involved:

- **Id:** Unique ID for each home sold
- **Date:** Date of the home sale
- **Price:** Price of each home sold
- **Bedrooms:** Number of bedrooms
- **Bathrooms:** Number of bathrooms, where .5 accounts for a room with a toilet but no shower
- **Sqft-living:** Square footage of the apartments interior living space
- **Sqft-lot:** Square footage of the land space
- **Floors:** Number of floors
- **Waterfront:** A dummy variable for whether the apartment was overlooking the waterfront or not
- **View:** An index from 0 to 4 of how good the view of the property was
- **Condition:** An index from 1 to 5 on the condition of the apartment
- **Grade:** An index from 1 to 13, where 1-3 falls short of building construction and design, 7 has an average level of construction and design, and 11-13 have a high quality level of construction and design.
- **Sqft-above:** The square footage of the interior housing space that is above ground level
- **Sqft-basement:** The square footage of the interior housing space that is below ground level
- **Yr-built:** The year the house was initially built
- **Yr-renovated:** The year of the house's last renovation
- **Zipcode:** What zipcode area the house is in
- **Lat:** Latitude
- **Long:** Longitude
- **Sqft-living15:** The square footage of interior housing living space for the nearest 15 neighbors
- **Sqft-lot15:** The square footage of the land lots of the nearest 15 neighbors

## 6 Empirical Analysis & Results

We now presents a thought process of predicting a continuous variable through applied machine learning methods.

More specifically, we want to predict house prices based on single and multiple features using regression analysis.

### 6.1 Exploratory Data Analysis EDA

We now explore the data set and study it's characteristics:

- Column Types: We change the data set columns to categorical data by using label encoder from sklearn
- Missing Values: We decided to drop them.
- Lengths and shapes: To see what's the amount of data that we are currently managing.

With a simple correlation, we can see that there are some variables with a higher correlation like the *sqft\_living* and some others like *zip\_code* or *id* or *longitude(earth)* have lower correlation.

Data Map Visualization

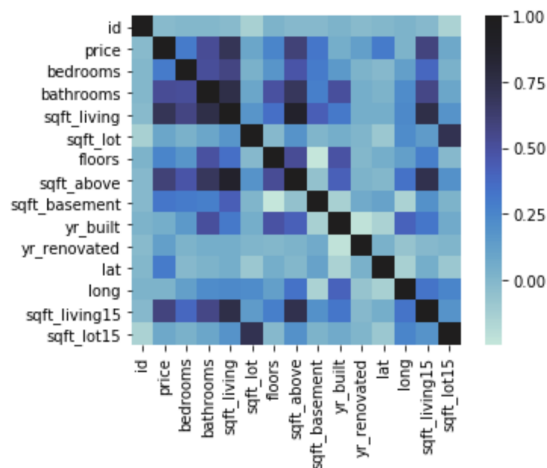


Figure 1: Heat Map of the correlations of some of the variables of the data set

We now look for the variables with the strongest correlation with price and study it in a boxplot dataset.

There seems to be a lot of outliers at the top of the distribution, with a few houses above the 5000000 value.

If we ignore outliers, the range is illustrated by the distance between the opposite ends of the whiskers (1.5 IQR) - about 1000000 here.

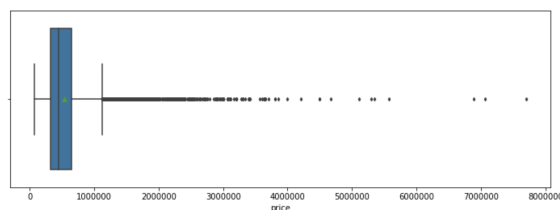


Figure 2: Box Plot of price in the data set.

Also, we can see that the right whisker is slightly longer than the left whisker and that the median line is gravitating towards the left of the box. The distribution is therefore slightly skewed to the right.

In figure 5, we can see the bi-variate relation of price in the data set.

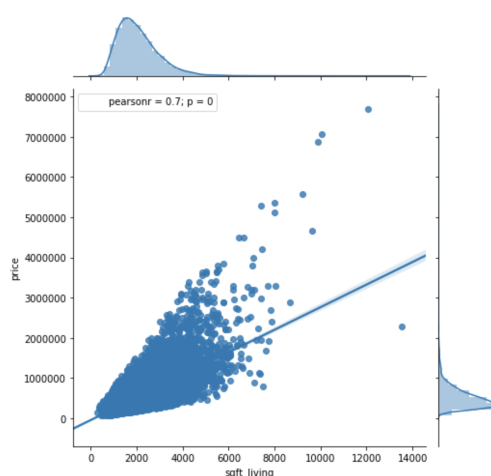


Figure 3: A joint plot of the bivariate distribution of our higher related variable

## 6.2 Regression Models & Preparation

We now will apply multiple regression models.

We will study the model complexity and try to make selections of the best predictive model using different model tuning variables, a validation set or cross-validation techniques.

We first start to split the model in two different sets: training and testing.

We select a Random State instance, random state is the random number generator; If `random_state=None`, the random number generator is the Random State instance used by `np.random`. But we select `random_state=0` to be able to replicate the training of our models.

The test size is 0.25 by default and we let it be like that.

## 6.3 Models

Now we start to train the different sklearn models with the training and scoring them with both splits training and testing.

### 6.3.1 Linear Models for Regression

In this section, we are going to use Liner Regression, Ridge's Regression and Lasso Regression, we study the difference when we applying the cost function.

The relevant formulas are as followed:

$$J_{(\theta)} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (6)$$

Linear cost function

$$J_{(\theta)} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda \sum_{i=1}^n w_i^2 \quad (7)$$

Rigde Cost Function

$$J_{(\theta)} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda \sum_{i=1}^n |w_i| \quad (8)$$

Lasso Cost Function

We now study the regression model with one feature.

Model	$R^2$ Test	$R^2$ Test
LinReg - One Feature	0.490	0.483
LinReg - All Features	0.703	0.69
Ridge Regr	0.702	0.691
Ridge Regr Scaled	0.696	0.681
Lasso Reg	0.703	0.69

Table 1: The results obtained with this cost functions applied to this models are seen in the data table

According to Table 1 & Figure 6, we can see that the best fit for our model is normal lineal regression with all features.

After applying the algorithm to predict instead of classify, we obtain that  $R^2$  is 0.537 (all features) and 0.462 for just one feature (*sqftliving*).

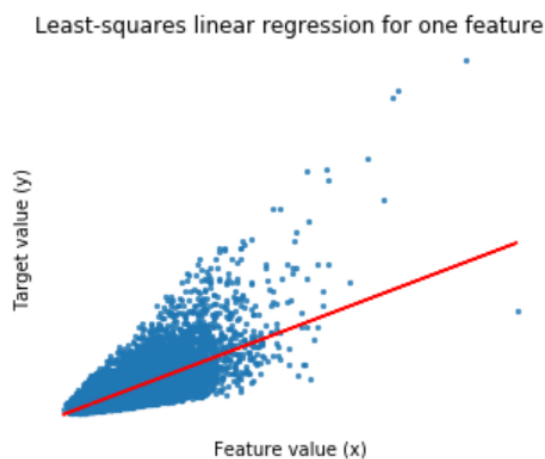


Figure 4: Graph of the linear regression for one feature

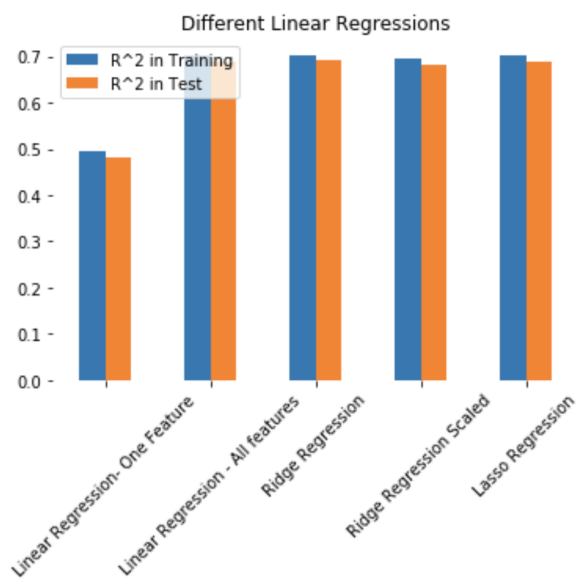


Figure 5: A bar representation of the scores of the different linear regression models

### 6.3.2 Multiple (Polynomial) Regression

In this section, we now study the data set to confirm if it fits better in a nonlinear function.

Model	$R^2$ Test	$R^2$ Test
LinReg	0.703	0.69
Pol Reg =2	0.700	0.660
Pol Reg=3	0.280	0.240
Pol Reg=2 + Ridge	0.644	0.449

Table 2: The results obtained with this cost functions applied to this models are seen in the data table.

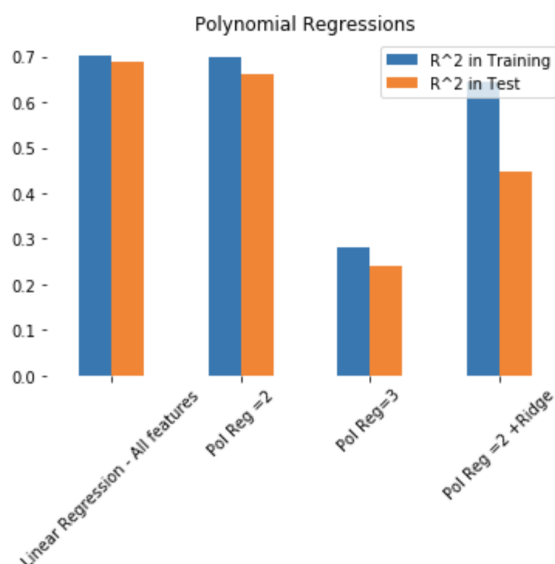


Figure 7: A bar representation of the scores of the different linear regression models

## 6.4 Ridge Regression and Lasso Alpha Parameter Tuning

Now, we will try to score the best options with Ridge and lasso regression. These regressions have the alpha/lambda parameter (eq7, eq8) that regularize the functions making them harder to overfit.

In figure 8 and figure 9, we can appreciate that Lasso and Ridge's regression work better for smaller alpha parameters.

## 6.5 k-Nearest Neighbors

We now start loading the model from the sklearn library to study K Nearest Neighbors of our data set.

We have trained 4 different models (classifier one feature, classifier all feature, regression one feature, regression all features). The results are shown in Table 5 and in Figure 10.

Model	$R^2$ Test	$R^2$ Test
Ridge Alpha=0.5	0.7	0.69
Ridge Alpha=1	0.7	0.69
Ridge Alpha=10	0.7	0.685
Ridge Alpha=20	0.7	0.681
Ridge Alpha=50	0.69	0.67
Ridge Alpha=100	0.67	0.652
Ridge Alpha=1000	0.44	0.432

Table 3: Results obtained for Ridge Alpha data table

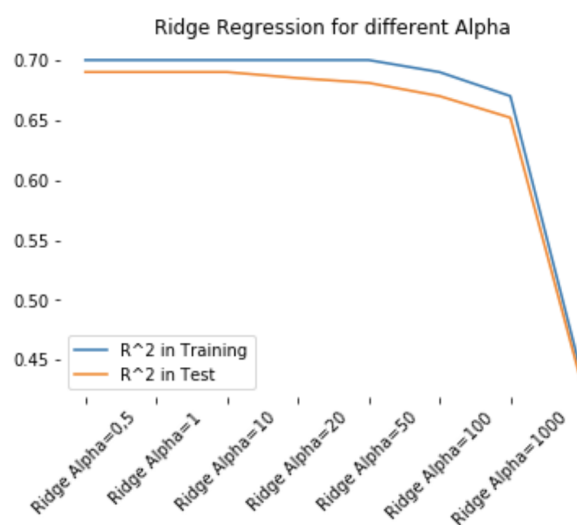


Figure 8: A simple plot of the score of Ridge's regression with different alpha parameters

Model	$R^2$ Test	$R^2$ Test
Lasso Alpha=10	0.7	0.69
Lasso Alpha=100	0.7	0.69
Lasso Alpha=500	0.69	0.68
Lasso Alpha=1000	0.69	0.68
Lasso Alpha=5000	0.61	0.61
Lasso Alpha=10000	0.48	0.48

Table 4: Results obtained for Lasso Alpha data table

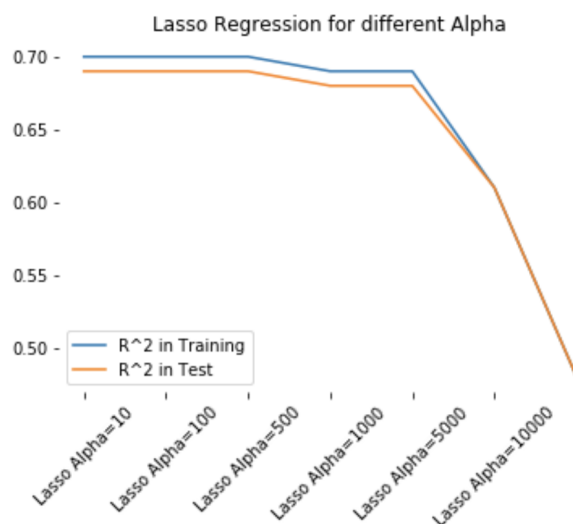


Figure 9: A simple plot of the score of Lasso's regression with different alpha parameters

	$R^2$ Test	$R^2$ Test		
Class - One Feature	0.04	0.005		
Class - All Features	0.18	0.01		
Regr - One Feature	0.45	0.458		
Regr - All features	0.410	0.357		

Table 5: Results obtained for k-Nearest Neighbors

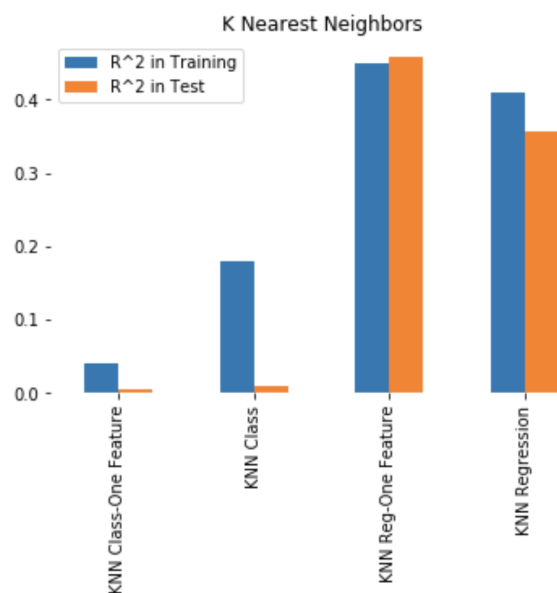


Figure 10: A bar representation of the scores of the different k-NN models



## 7 Discussion and Conclusions

### 7.1 Models

For **k-NN** We started by applying the algorithm to predict classify instead of predict, so we obtained pretty low scores. With the prediction algorithm we get an  $R^2 = 0.36$  (all features) and 0.458 for just one feature (sqft-living). It works better with just one feature. We have achieve almost 50% of predicting prices with just one variable in k-NN regression. And after studying the graphical representation, we can see that the best k-NN neighbors parameter is  $k = 3$  with we obtain a  $R^2 = 0.536$ .

Also we have applied the **polynomial regressions** of degree 2 and 3, we can see that the performance of the model is better with linear regression than with any higher order polynomial.

For **Ridge and Lasso** regression we could see that the model doesn't work much better than linear regression for this case. We have obtained best results for Lasso (regression) of  $R^2 = 0.69$ . And the best alpha parameter is between 1 – 500. This shows that the low alphas the results are better. For instance, when the alpha value is 0, Lasso (regression) produces the same coefficients as a linear regression. When alpha is very large, all coefficients are zero. We can say that our data in our model behaves linearly.

Applying the k-NN class, k-NN regression, linear, linear ridge, linear lasso, linear one feature, linear ridge one feature, square regression, square with ridge, cubic regression and cubic regression with ridge, we can see that **the best model is linear regression with all features**.

### 7.2 Conclusion

Within this report, we have conducted an empirical study to give on overview of regression methods using the given data set.

We have studied the Simple Regression, Multiple (Polynomial) Regression, Ridge Regression, Gradient Descent, Lasso, Coordinate Descent and k-Nearest Neighbors algorithms and models.

There is many more algorithms and/or models to used i.e. Elastic Net, Kernel Regression, Bayesian Regression, Support Vector Machine (using classification and/or regression analysis), Artificial Neural Network, Convolutional Neural Network, Random Forest, Decision Tree etc.

Based on the study of the python implementations developed, we can see that the information given after a small data treatment behaves linearly. After researching in different Kernels we have seen that the best models are able to predict with an  $R^2 = 0.77$  with feature engineering and an  $R^2 = 0.85$  with deep learning techinques.

However, at this moment, we are satisfied with our overall results to have achieved  $R^2 = 0.700$  from our test data set without applying any extremely difficult and/or complex Artificial Intelligence algorithm.

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