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# HOUSE PRICES

## ADVANCED REGRESSION TECHNIQUES

# California State University, Los Angeles

A Report on-  
House Prices: Advanced Regression  
Techniques

Under course-  
CS4661: Introduction to Data Science

Submitted To-  
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# 1. Project Description and Details

In this project we are trying to predict house prices depending on different variables using regression techniques. The main purpose of it is that the buyers can get an idea of the house prices in which they like or are trying to purchase.

## 2. Project Goals

The project goal is to get better pricing of houses with our developed methods and algorithms. Also, to try and get the accuracy of our developed methods to be as near to the data as possible.

## 3. Data Details

MSSubClass: The building class

MSZoning: The general zoning classification

LotFrontage: Linear feet of street connected to property

LotArea: Lot size in square feet

Street: Type of road access

Alley: Type of alley access

LotShape: General shape of property

LandContour: Flatness of the property

Utilities: Type of utilities available

LotConfig: Lot configuration

LandSlope: Slope of property

Neighborhood: Physical locations within Ames city limits

Condition1: Proximity to main road or railroad

Condition2: Proximity to main road or railroad (if a second is present)

BldgType: Type of dwelling

HouseStyle: Style of dwelling

OverallQual: Overall material and finish quality

OverallCond: Overall condition rating

YearBuilt: Original construction date

YearRemodAdd: Remodel date

RoofStyle: Type of roof

RoofMatl: Roof material

Exterior1st: Exterior covering on house  
Exterior2nd: Exterior covering on house (if more than one material)  
MasVnrType: Masonry veneer type  
MasVnrArea: Masonry veneer area in square feet  
ExterQual: Exterior material quality  
ExterCond: Present condition of the material on the exterior  
Foundation: Type of foundation  
BsmtQual: Height of the basement  
BsmtCond: General condition of the basement  
BsmtExposure: Walkout or garden level basement walls  
BsmtFinType1: Quality of basement finished area  
BsmtFinSF1: Type 1 finished square feet  
BsmtFinType2: Quality of second finished area (if present)  
BsmtFinSF2: Type 2 finished square feet  
BsmtUnfSF: Unfinished square feet of basement area  
TotalBsmtSF: Total square feet of basement area  
Heating: Type of heating  
HeatingQC: Heating quality and condition  
CentralAir: Central air conditioning  
Electrical: Electrical system  
1stFlrSF: First Floor square feet  
2ndFlrSF: Second floor square feet  
LowQualFinSF: Low quality finished square feet (all floors)  
GrLivArea: Above grade (ground) living area square feet  
BsmtFullBath: Basement full bathrooms  
BsmtHalfBath: Basement half bathrooms  
FullBath: Full bathrooms above grade  
HalfBath: Half baths above grade  
Bedroom: Number of bedrooms above basement level  
Kitchen: Number of kitchens  
KitchenQual: Kitchen quality  
TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)  
Functional: Home functionality rating  
Fireplaces: Number of fireplaces  
FireplaceQu: Fireplace quality  
GarageType: Garage location  
GarageYrBlt: Year garage was built  
GarageFinish: Interior finish of the garage  
GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet  
GarageQual: Garage quality  
GarageCond: Garage condition  
PavedDrive: Paved driveway  
WoodDeckSF: Wood deck area in square feet  
OpenPorchSF: Open porch area in square feet  
EnclosedPorch: Enclosed porch area in square feet  
3SsnPorch: Three season porch area in square feet  
ScreenPorch: Screen porch area in square feet  
PoolArea: Pool area in square feet  
PoolQC: Pool quality  
Fence: Fence quality  
MiscFeature: Miscellaneous feature not covered in other categories  
MiscVal: \$Value of miscellaneous feature  
MoSold: Month Sold  
YrSold: Year Sold  
SaleType: Type of sale  
SaleCondition: Condition of sale

Data Sets: test.csv (1459 X 80)  
              train.csv (1460 X 81)

Note: The [Ames Housing dataset](#) was compiled by Dean De Cock for use in data science education. It's an alternative for data scientists looking for a modernized and expanded version of the often cited Boston Housing dataset.

## 4. Developed Methods, Algorithms and Tools

We used methods from the libraries namely scikit learn, pandas, numpy.

We used pandas read\_csv() method to read the train.csv and test.csv data files.

We used scikit's preprocessing.scale() method to normalize the data.

We used LogisticRegression() 's fit method to train the data, its predict method to predict the data and accuracy\_score() method to get the accuracy.

We used DecisionTreeClassifier() 's fit method to train the data, its predict method to predict the data and accuracy\_score() method to get the accuracy.

We used KNeighborsClassifier() with k=3 's fit method to train the data, its predict method to predict the data and accuracy\_score() method to get the accuracy.

We used RandomForestRegressor with max\_depth=2, random\_state=0, n\_estimators=100 's fit method to train the data, its predict method to predict the data and explained\_variance\_score() method to get the accuracy.

Also we created methods such as

1. createValues()- to handle NaN values.
2. createSaleCondition\_Normal(a)-to convert categorical SaleCondition\_Normal to numerical
3. createSaleCondition\_Abnormal(a)- to convert categorical SaleCondition\_Abnormal to numerical
4. createSaleCondition\_Partial(a)- to convert categorical SaleCondition\_Partial to numerical
5. createSaleCondition\_AdjLand(a)- to convert categorical SaleCondition\_AdjLand to numerical
6. createSaleCondition\_Family(a)- to convert categorical SaleCondition\_Family to numerical
7. createSaleCondition\_Aloc(a)-to convert categorical SaleCondition\_Aloc to numerical

## 5. Results

Accuracy using Logistic Regression is 0.005479452054794521

Accuracy using Decision Tree is 0.0136986301369863

Accuracy using KNN Classifier is 0.00821917808219178

Accuracy using Random Forest Regression is 0.40399259640650076

## **6. Performance Analysis**

From these results, we came to the conclusion that Random Forest Regression is the best for our data and Logistic Regression is the worst.

## **7. Responsibility of Team Members**

We split up the work equally so that everyone could get a chance to work on algorithms, functions, project paper, and the power point slides. This made the project go smoother.