

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

House Price Prediction Using Machine Learning

Robbi Jyothsna

Student, Department of Information Technology, GMR Institute of Technology, Rajam, India

ABSTRACTION

There is a rise in demand for renting a house and buying house therefore, determining a more efficient to calculate the house rents is crucial. House rent increases once a year, So there's a desire to predict house rents within the future. House rent prediction has gained lots of focus nowadays. House rent prediction system studies behaviour of your time series data and reflects the long run rents. Forecasting foreign countries is vital to understand the house trends in an exceedingly particular country. Software implementations for the experiment were selected from python libraries. Data preprocessing and preparation techinques so as to get clean data. To make machine learning models ready to predict house price supported house features to research and compare models performance so as to decide on the simplest model. We applied three different Machine Learning algorithms: Decision tree, Random forest and XG Bootsting on the training data

Keywords: Machine Learning, Linear Regression, Decision tree, Random forest,

INTRODUCTION

Due to the increase in urbanization, there is an increase in demand for renting houses and purchasing houses. Due to the heterogeneous nature of housing and the thin housing market with infrequent transactions, the house rents determination process is inappropriate. Therefore, to determine a more effective way to calculate house rents that accurately reflects the market 12 prices in the future also. There are various factors that influence the prediction price of a house which include physical conditions, transportation, concept, and location, etc.... Therefore, an accurate prediction of housing rents is important here, we will introduce you to a house rental prediction system (HRPS). HRPS system improves prediction accuracy and predicts future house rents. The system provides several things such as

- To know the trend of house rents in a certain location.
- For renting houses.
- To fill the information gap by avoiding the third person.
- To predict the prices according to the locality.
- To predict the house rents in the upcoming future and can plan to shift to a particular location by knowing the house rents in a locality.
- The HRPS system provides the foreign region with future house rents which can be helpful for those people out of those countries, so they can know the house rents of a particular foreign country.
- To know the house rents of the foreign country regions and their future house rents

LITERATURE SURVEY:

- 1. [Maryam Heidari, Samira Zad, Setareh Rafatirad; 2021] Real-Estate rent prediction in housing marketing research plays a key role in conniving the speed of come back a salient index wont to appraise real-estate investment choices. correct rent prediction in property investment will facilitate in generating capital gains and guarantee a money success. during this paper, we stock out a comprehensive analysis and study of seven machine learning algorithms for rent prediction, together with regression, Multilayer Perceptron, Random Forest, KNN, domestically Weighted Learning, SMO, and KStar algorithms. we have a tendency to train new models for the USA territory, together with 3 house kinds of single-family, townhouse, and condo. every knowledge instance within the dataset has twenty one internal attributes (e.g., area space, price, variety of bed/bathroom, rent, faculty rating, so forth). A set of the collected options designated by filter ways for the prediction models
- 2. [Hao Peng, Jianxin Li, Zheng Wang, Renyu Yang, Mingsheng Liu, Mingming Zhang, Philip Yu, Lifang He; 2021] we have a tendency to gift LUCE, the primary life-long prognostic model for machine-driven property valuation. LUCE addresses 2 vital problems with property valuation: the dearth of recent oversubscribed costs and therefore the scantiness of house knowledge. it's designed to control on a restricted volume of recent house transactions. As a departure from previous work, LUCE organizes the house knowledge in a very cubic content unit wherever graph nodes are house entities and attributes that are vital for house value valuation. we have a tendency to use GCN to extract the abstraction info fourteen from the cubic content unit, so use the LSTM network to model the temporal dependencies over time. not like previous work, LUCE makes effective use of the restricted house transactions within the past few months to update valuation info for all house

entities

- 3. [Mansi faith, Himani Hindu, Neha Garg, Pronika Chawla; 2020] This paper provides an summary concerning the way to predict house prices utilizing totally different regression ways with the help of python libraries. The projected technique thought-about the additional refined aspects used for the calculation of house value and provided a additional correct prediction. It conjointly provides a quick concerning varied graphical and numerical techniques which is able to be needed to predict the worth of a house. This paper contains what and the way the house rating model works with the assistance of machine learning and that dataset is employed in our projected model.
- 4. [Quang Truong, Minh Nguyen, Hy Dang, Bo Mei; 2020] House indicator (HPI) is often accustomed estimate the changes in housing worth. Since housing worth is powerfully related to different factors like location, area, population, it needs different data with the exception of HPI to predict individual housing worth. There has been a significantly sizable amount of papers adopting ancient machine learning approaches to predict housing costs accurately, however they seldom concern regarding the performance of individual models and sixteen neglect the less fashionable nonetheless complicated models. As a result, to explore numerous impacts of options on prediction strategies, this paper can apply each ancient and advanced machine learning approaches to research the distinction among many advanced models.
- 5. [Feng Wang, Yang Zou, Haoyu Zhang, Haodong Shi; 2019] The nonlinear relationship between powerful factors and house worth and inadequate variety of sample sizes may be the reason for the poor performance of the normal models. Meanwhile, the daily information of the \$64000 estate market is extremely vast and it's increasing chop-chop. the normal house worth prediction approaches lack capability for large information analysis, inflicting low utilization of information. to deal with these considerations, a house worth prediction model supported deep learning is planned during this paper, enforced on the TensorFlow framework. Adam optimizer is employed to coach the model, wherever the Relu operate is adopted to be the activation operate. Then the house worth trend is expected supported the ARIMA model.

Introduction to Machine Learning:

Machine learning could be a subfield of artificial intelligence(AI). The goal of machine learning typically is to grasp the structure information of knowledge of information and work that data into modules which will be understood and used by people.

Although machine learning could be a field inside technology, it differs from ancient process approaches. In ancient computing ,algorithm are sets of expressly programmed directions utilized by computers to calculate or downside solve. Machine learning algorithms instead afford computers to coach on knowledge inputs and use applied mathematics analysis facilities computers in building models from sample knowledge so as to alter decision-making processes supported knowledge inputs

Machine Learning could be a continuous developing field. attributable to this, there are some concerns to stay in mind as you're employed with machine learning methodologies, or analyze the impact of machine learning method.

Machine Learning could be a term closely related to knowledge science . It refers to a broad category of ways that revolves around knowledge modelling to:

- (1) Supervised Learning : to algorithmically build predictions, and
- (2) Unsupervised Learning: to algorithmically decipher patterns in knowledge

Supervised Machine Learning:

It is used for structures datasets. It analyses the coaching knowledge and generates operations which is able to be used for different datasets. it's Machine Learning for creating predictions-Core idea is to use labeled knowledge to coach prognostic models. coaching models suggests that mechanically characterizing labelled knowledge in ways that to predict tags for unknown knowledge points. for instance a master card fraud detection model may be trained employing an account of labelled fraud purchases. The resultant model estimates the chance that any new purchase is deceitful. Common ways for coaching models vary from basic regressions to advanced neural nets. All follow identical paradigm grasp as supervised learning

3.1 Machine learning techniques used:

Linear Regression- It may be a renowned fashionable formula in machine learning and statistics. This model can assume output variable. It is depicted within the kind of equation linear relationship between the input and also the output variable. It is depicted within the kind of equation that includes a set of inputs and a prognosticative output. Then it'll estimate the values of constant utilized in the illustration

In ML, we've a group of inputs variables(x) that area unit accustomed verify the output variable (y) .A relationship exists between the input variables and output variable. The goal of cubic centimeter is to quantify this relationship



In regression, the connection between the input variables(x) ANd output variable (y) is expressed as an equation of the shape y=a+bx. Thus, the goal of regression is to seek out out the values of coefficients a and b. Here ,a is that the intercept and b is that the slope of the line

The fig shows the premeditated x and y values for a dataset. The goal is to suit a line that's nearest to most of the points . this may scale back the gap ('error) between the y worth of a knowledge purpose and also the line

The regression estimates area unit accustomed make a case for the connection between one variable and an extra variable quantity . the only kind of the equation with one dependent and one variable quantity is outlined by the formula y=c+b*x, wherever y is that the calculable variable score, c=constant, b=regression constant, and x=score on the variable quantity

Simple regression may be a statistical procedure that enables United States to summarize and study realtionships between 2 continuous (quantitative)variables:

- (1) Simple linear regression: 1 variable (interval or ratio), one freelance variable(interval or ration or dichotomous)
- (2) Multiple linear regression: one variable (interval or ratio), 2+independent variable(interval or ration or dichotomous)
- (3) Logistic regression: one variable (interval or ratio), 2+ freelance variable(s)(interval or ration or dichotomous)
- (4) Multinomial regression: one variable (nominal), 1+ freelance variable(s)(interval or ration or dichotomous)
- (5) Discriminant analysis : one variable (nominal), 1+ freelance variable(s)(interval or ration)

Logistic Regression – Logistic regression is best suited to binary classification(datasets wherever y=0 or one, wherever one denotes the default category. Example: in predicting whether or not an occurrence can occur or not, the event that it happens is assessed as one. In predicting whether or not an individual is sick or not, the sick instances are denoted as 1). It is named once the transformation performs used it, known as the logistical perform

Support Vector Classifier-. SVM is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used for classification problems. In this algorithm, we plot each data items as a point n-dimensional space(where n is number of features you have)with the value of each features being the value of a particular coordinate. Then, we perform classification by finding the hyperplane(in two dimentional space it is classifier line, mostly strait)that differentiate the two classes (groups of data)very well



Supper Vector are merely the co-ordinates of individual observation. Support Vector Machine could be a frontier that best segregates the 2 categories (hyper-plane/line) the method of segregation the 2 categories with hyperplane. Support vector machine (SVM) once your information has precisely 2 categories. associate SVM categories information by finding the simplest hyperplane that separates all information points of 1 category from those of the opposite class. The best hyperplane for associate SVM means the one with the massive margin between the 2 categories. Margin means that the largest breadth of the block parallel to the hyperplane that has no interior information points

K-Nearest Neighbor – K-nearest neighbor classifier is one amongst the introductory supervised classifiers, which every information science learner ought to remember of. Fix & Hodge planned a K-nearest neighbor classifier formula within the year of 1951 for the playacting pattern classification task The simple version of the K-nearest neighbor. classifier algorithm is to predict neighbor classifier algorithms is to predict the target label by finding the closest neighbor category. The highest category is going to be known as exploitation of the gap live like Euclidian distance The k-nearest neighbor formula may be a pattern recognition model which will be used for classification yet as regression. usually abbreviated as k-NN, the k-nearest neighbor may be a positive whole number, that is usually little.In either classification or regression, the input can consist of the k nearest coaching example inside an area the output is class membership. This will assign a new object to the class most common among its k nearest neighbors.



When a new object is intercalary to the space-in this case a inexperienced heart-we can wish the machine learning rule to classify the center to a particular after



We select k=3, the rule can notice the 3 nearest neighbors of the inexperienced heart so as to category if it to either the diamond category or the star class In our diagram, the 3 nearest neighbors of the inexperienced heart one diamond and 2 stars. Therefore, the rule can category if y the center with the star class



Among the foremost basic of machine learning algorithms, the k-nearest neighbor is taken into account to be a kind of "lazy learning" as the generalization on the far side the coaching knowledge doesn't occur till a question is formed to the system

Random Forest – is Associate in Nursing extension over sacking. It takes one further step wher additionally to taking the random set of information, it conjointly takes the random choice of options instead of victimization all options to grow hair style. after you have several random trees. It's known as Random Forest.

Steps taken to implement Random Forest:

- 1. 1.Suppose there square measure N observations and M options in coaching knowledge set.First, a sample from coaching knowledge set is taken every which way with replacement
- 2. A set of M options square measure designated every which way and whichever feature offers the simplest split is employed to separate the node iteratively
- 3. The tree is big to the biggest
- 4. Above steps square measure perennial and prediction is given supported the aggregation of predictions from n variety of trees

Random Forest may be a versatile machine-learning methodology capable of playacting each regression and classification tasks. It conjointly undertakes dimensional reduction ways, treats missing values, outliers values, and different essential steps of information exploration. it's a kind of ensemble learning methodology, wherever a bunch of weak modules combines to make a strong model

In Random Forest, we have a tendency to grow multiple trees as opposition one tree in CART model. To classify a replacement object supported Associate in Nursing attribute, every tree offers a categoryification and that we say the tree "votes" for that class. The forest chooses the classification having the foremost votes(over all the trees within the forest) and just in case of regression, it takes the common of outputs by completely different hair styleDesigning Machine Learning Algorithms:

The following are the ingradients of style procedure:

- Check Harnessing: you wish to outline a check hardness. The check harness is that the knowledge you'll train associated check an algorithmic
 rule against and therefore the performance live you'll use to assess its performance. it's necessary to outline your check harness well so you'll
 concentrate on evaluating completely different algorithms and thinking deeply concerning the matter
- 2. **Performance Measure:** The performance live is that the means you would like to judge an answer to the matter. it's the measuring you'll create of the predictions created by a trained model on the check knowledge set
- 3. Testing and coaching Datasets: From the remodeled knowledge, you'll have to be compelled to choose a check set and a coaching set. associate algorithmic rule are trained on the coaching dataset and can be evaluated against the check set. this might be as straightforward as choosing a random split of data(70% for coaching,30% for testing) or could involve a lot of difficult sampling strategies.
- 4. Cross Validation: A lot of subtle approach than employing a check and train knowledge set is to use the whole remodeled knowledge set to coach and check a given algorithmic rule. a way you'll use in your check harness that will this is often known as cross-validation

PROPOSED WORK

The purpose of this method is to work out the value of a house by watching the varied options that are given as input by the user. These options are given to the cubic centimetre model and supported however these options have an effect on the label it offers out a prediction. this may be done by 1st looking for an associate degree applicable dataset that suits the wants of the developer additionally because of the user. moreover, once finalizing the dataset, the knowledge set can bear the method referred to as data cleansing wherever all the data that isn't required are going to be eliminated and therefore the {raw knowledge|data|information} are going to become a .csv file. Moreover, the information can go through knowledge pre-processing wherever missing knowledge are going to be handled and if required label cryptography are going to be done. Moreover, this will bear knowledge transformation wherever {it can|it'll} be born-again into a NumPy array so it will finally be sent for coaching the model. whereas coaching varied machine learning algorithms are going to be accustomed train the model their error rate is going to be extracted associate degreed consequently an rule and model are going to be finalized which might yield correct predictions. Users and companies are going to be able to log in and so fill a kind regarding varied attributes of their property that they require to predict the price of. in addition, once a radical choice of attributes, the shape are going to be submitted. This knowledge entered by the user will then attend the model and at intervals of seconds the user are going to be able to read the expected worth of the property that they place in

FLOW CHART:



Fig.1 Data Flow Diagram

METHODOLOGY

import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns import sklearn.datasets from sklearn.model_selection import train_test_split

Fig.2 Importing the standard libraries which we required

df=sklearn.datasets.load_boston()

Fig.3 Loading Boston house dataset

[] df1-pd.DataFrame(df.data,columns-df.feature_names)

```
[] df1
```

| | CRIM | ZN | INDUS | CHAS | NOX | 用州 | AGE | DIS | RAD | TAX | PTRATIO | 9 | LSTAT |
|-------|-----------|--------|-------|------|-------|-------|------|--------|-----|-------|---------|--------|-------|
| 0 | 0.00632 | 18.0 | 2.31 | 0.0 | 0.538 | 6.575 | 65.2 | 4.0900 | 1.0 | 296.0 | 15.3 | 396.90 | 4.90 |
| 1 | 0.02731 | 0.0 | 7.07 | 0.0 | 0.469 | 6.421 | 78.9 | 4.9871 | 2.0 | 242.0 | 17.8 | 396.90 | 9,14 |
| 2 | 0.02729 | 0.0 | 7.07 | 0.0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2.0 | 242.0 | 17.8 | 392.83 | 4,03 |
| 3 | 0.03237 | 0.0 | 2.18 | 0.0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3.0 | 222.0 | 18.7 | 394.63 | 2.94 |
| 4 | 0.06905 | 0.0 | 2.18 | 0,0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3,0 | 222.0 | 18,7 | 396.90 | 5,33 |
| , în | | 1044 | - 55 | | 1.062 | 30 | 10 | 1.000 | - | 1.00 | - | 94 | 1.00 |
| 501 | 0.06263 | 0.0 | 11.93 | 0.0 | 0.573 | 6.593 | 69.1 | 2,4786 | 1.0 | 273.0 | 21.0 | 391,99 | 9,67 |
| 502 | 0.04527 | 0.0 | 11.93 | 0.0 | 0.573 | 6.120 | 76.7 | 2.2875 | 1.0 | 273.0 | 21.0 | 396.90 | 9.06 |
| 503 | 0.06076 | 0.0 | 11,93 | 0.0 | 0.573 | 6.976 | 91.0 | 2.1675 | 1.0 | 273.0 | 21.0 | 396.90 | 5.64 |
| 504 | 0.10959 | 0.0 | 11.93 | 0.0 | 0.673 | 6.794 | 89.3 | 2.3889 | 1.0 | 273.0 | 21.0 | 393.45 | 6.48 |
| 505 | 0.04741 | 0.0 | 11.93 | 0.0 | 0.573 | 6.030 | 80.8 | 2.5050 | 1.0 | 273.0 | 21.0 | 396.90 | 7.88 |
| 506 m | ws × 13 o | olumns | | | | | | | | | | | |

Fig. 4 Boston house price dataset

| [] | df1[" df1[' | price"] price'] | -df.targ | et | | | |
|----|-------------------------------------------|----------------------------------------------------|----------|------|--------|---------|--|
| | 0 1 2 3 4 | 24.0 21.6 34.7 33.4 36.2 | | | | | |
| | 501 502 503 504 505 Name : | 22.4 20.6 23.9 22.0 11.9 price, | Length: | 506, | dtype: | float64 | |

Fig. 5 Target Variable in the dataset

| 0 | df1.isnul | 1().sum() | | |
|----|-----------|-----------|--|--|
| D- | CRIM | 0 | | |
| - | 294 | 0 | | |
| | INDUS | 0 | | |
| | CHAS | 0 | | |
| | NOX | 0 | | |
| | RM | 0 | | |
| | AGE | 0 | | |
| | DIS | 0 | | |
| | RAD | 0 | | |
| | TAX | 0 | | |
| | PTRATIO | 0 | | |
| | в | 0 | | |
| | LSTAT | 0 | | |
| | price | 0 | | |
| | dtype: in | t64 | | |

Fig.6 Null values in the dataset

| oleviati). Mer | ine() | | | | | | | | | | | | | |
|-------------------|-----------|-----------|------------|------------|-----------|-----------|------------|-------------|-----------|-----------|-----------|-----------|-----------|------------|
| | 008 | 19 | 200.0 | 1046 | - | | Alt | - 101 | 140 | 105 | enurse | | sater | price |
| CRM | 1.0000 | 1,200400 | 14000 | 4 (1996) | 3-42071 | 421047 | 1.002734 | 4179670 | A Append | 1.002704 | 1,200+0 | 1.385394 | 8-40021 | -0.399316 |
| 214 | -0.210489 | 1.000446 | 4.00629 | -0.0428887 | -2.579834 | 0.211001 | -2.5845.17 | 0.984408 | -0.211948 | 431400 | 4.39579 | 0179520 | -0.412965 | 0.00440 |
| INDUS | 1.416781 | -12030 | 1.00000 | 0.042918 | 376401 | 4.91976 | 5.044772 | -0.708027 | 0.046129 | 1.720790 | 1.9024 | -0.200077 | 0.0000 | 4.463725 |
| OWS | -0.755842 | 4042687 | 0.042508 | 1.142228 | 1.01203 | 5.041231 | 5.080715 | 4088179 | 0.007388 | 4.000007 | 4.121815 | 0.040782 | 4103828 | 0.175280 |
| HOX | 5.421872 | - | 6.793401 | 0.091208 | 1.000000 | -0.002108 | 8.731470 | -1.748020 | | 1.008523 | 0.1680033 | -0.300081 | 0.00079 | 41427521 |
| *** | 42986 | 0.011001 | 4.001078 | 0.081251 | 4.8218 | 1,000000 | -0.24586 | 0.215240 | 4220647 | -0.292048 | 4.100801 | 0.128848 | -2.013608 | 1-110300 |
| A08 | 0.352734 | -11000 | 1.844779 | 0.00016 | 5,721470 | 4.24088 | 1,000000 | -4.747881 | 1.49022 | 1.00416 | 6201018 | -22710314 | 0.0022390 | 4.376866 |
| 018 | -0.379870 | 0.084418 | 4.70807 | 4.088176 | 4.765230 | 0.00546 | -0.747881 | 1.000080 | -0.404100 | -0.556432 | 0.253471 | 0.001012 | 4.48000 | 0.248828 |
| RAD | 3.421008 | -0.211948 | 5.08129 | 4.007068 | 3(01)44) | -520947 | 0.499032 | 4444 | 1.000000 | 0.010200 | 2.404741 | - | 0-408279 | 4.381928 |
| 54.8 | 0.882784 | -0.214585 | 8.735760 | -0.5799897 | 1.000023 | -125514 | 1.508456 | -11.5394522 | 0.01000 | 1,00000 | 0.403403 | -barrala | 0.042891 | J. elatite |
| PTRATIO | 1.222048 | <381879 | 1.10248 | 4121019 | 110003 | -0.000001 | 1.201010 | -0.253471 | (240474) | 0.400003 | 1.00000 | -4.17180 | 0.374044 | 4.90792 |
| | -1.107034 | 0.175520 | -6.3586977 | 0.040786 | -0.580001 | 0.128080 | -0.373834 | 6,291512 | -1.444415 | -0.041030 | -0.177383 | 1/000000 | -0.389387 | 0.333461 |
| LENT | 11410821 | 4.412946 | 0.809804 | 4.00000 | 1.00079 | -2413818 | 1.4127.08 | -0.496906 | 0.488679 | 124000 | 0.574044 | 4,000007 | 1.000006 | 4.737966 |
| price | -0.548308 | 6.00046 | -0.480725 | 4.170200 | 4417471 | 0.4940360 | 4.376955 | 0.2+9909 | -1.381626 | -1.00000 | 4.007987 | 0.3379491 | -0.737983 | 1.000000 |

Fig.7 Correlation

| 12 | 100 | | | | | | | | | | |
|-------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------|-------------|------|----------|-------|------|--------|-----|-------|---|
| | 100 | 1 | - | | | | | | | 1 | 1 |
| | 4.400 | 12.4 | 4.05 | 1.4 | 8.14 | 4.10 | 10.3 | | 1.0 | 10.5 | |
| 1.1 | 4.60755 | | 1.45 | 10 | 8.44 | 6.405 | 19-1 | 4,0070 | 2.4 | 293,8 | |
| ÷. | 4.40728 | 22 | 1.10 | 22 | 1.144 | 122 | 2.5 | 1.000 | 12 | 22.4 | |
| | a animi | 4.4 | 1.18 | 31.0 | 0.014 | 1.60 | 14.3 | 0.0010 | 1.4 | 228,4 | |
| 14 | 1000 | - | 10.00 | | 4.10 | 4,000 | - | 1.00 | 1.0 | 10.4 | |
| 100 | 11-04111 | - | 10.300 | 0.4 | (0, 1/2) | FLGB | 10,1 | 4.0875 | 1.4 | 111.4 | |
| 123 | A. A0211 | - 22 | 11.11 | -22 | 10,000 | 1.11 | 11.5 | 1.107 | 12 | 10.4 | |
| - | 1.46140 | 1.0 | 10.00 | - 64 | 8.319 | 1.1.0 | 10.4 | 1,1010 | 12 | 111.4 | |
| | 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月1日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月11日 11月111 11月111 11月111 11月111 11月111 11月111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 11月1111 111111 | 「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、「二日二」、 | 1211-122222 | | | | | | | | |
| [500 | rows | * 1 | 13 co | lum | ns] | | | | | | |
| | 21 | | | | | | | | | | |
| 5 | 1.1 | | | | | | | | | | |
| 2 | 21 | ÷. | | | | | | | | | |
| | - 24 | | | | | | | | | | |
| - | - 15 | | | | | | | | | | |
| | | · . | | | | | | | | | |
| 2471 | - 11 | - 7 | | | | | | | | | |
| 562 | 20 | -0 | | | | | | | | | |
| 563 | 23 | -9 | | | | | | | | | |
| 584 | - 22 | -87 | | | | | | | | | |
| 1.012 | | 100 | | | | | | | | | |

Fig.8 Drop and assign X, Y Variables





100

Regression Metrics:

midel acviency: 73,47454846256315

The following three are the most common metrics for evaluating predictions on regression machine learning problems:

- 1. *Mean Absolute Error:* is the sum of the absolute difference between predictions and actual values. It gives an idea of how wrong the predictions were. The measure gives an idea of the magnitude of the error, but no idea of direction(e.g. over or under-predicting).
- 2. Mean Squared Error(MSE):MSE is much like the mean absolute error in that it provides a gross idea of the magnitude of error. It is a measure of the difference between two continuous variables. Assume X and Y are variables of paired observations that express the same phenomenon. Examples of Y versus X include comparisons of predicted versus observed, subsequent time versus initial time, and one technique of measurement versus an alternative technique of measurement. Consider a scatter plot of n points, where point I has coordinates .Mean Absolute Error(MSE) is the average vertical distance between each point and the Y=X line, Which is also known as the One-to-one line MAE is also the average horizontal distance between each point and the line Y=X line
- 3. *R-Squared Metric*: the R-Squared metric provides an indication of the goodness of fit of a set of predictions to the actual values. In statistical literature, this measure is called the coefficient of determine. This value between 0 and 1 for no-fit and perfect fit respectively

RESULTS

Streamlit is AN open supply python primarily based framework for developing and deploying interactive knowledge science dashboards and machine learning models. this suggests that you simply don't ought to have confidence a team of front developers or pay giant amounts of your time learning netstyle languages like markup language, CSS or Javascript so as to deploy your dashboard or model. Streamlit was supported in 2018 by ex-Google engineers United Nations agency gained 1st hand expertise of the challenges two-faced once developing and deploying machine learning models and dashboards.

It is designed on top of Python and supports several of the thought Python libraries like matplotlib, Ploty and Pandas



CONCLUSION

Buying your own home is what each human wants for. exploitation this planned model, we would like folks to shop for homes and property at their rightful costs and need to confirm that they do not get tricked by uncomplete agents United Nations agency simply area unit once their cash. to boot, this model also will facilitate massive corporations by giving correct predictions for them to line the valuation and save them from loads of trouble and save loads of precious time and cash. Correct property costs area unit the essence of the market and that we need to confirm that by exploiting this model. The system is apt enough in coaching itself and in predicting the costs from the data provided to that. once looking many analysis papers and various blogs and articles, a collection of algorithms were selected that were appropriate in applying on each the datasets of the model. once multiple testing and coaching sessions, it absolutely was determined that the Linear Regression algorithmic rule showed the most effective result amongst the remainder of the algorithms. The system was potent enough for Predicting the costs of {various} homes with various options and was ready to handle massive sums of information. The system is kind of easy and time-saving.

REFERENCES:

- Maryam Heidari;Samira Zad;Setareh Rafatirad; (2021). Ensemble of Supervised and Unsupervised Learning Models to Predict a Profitable Business Decision . 2021 IEEE International IOT, Electronics and Mechatronics Conference (AIMTRONICS), (), -. doi:10.1109/iemtronics52119.2021.9422649
- [2]. Pei-Ying Wang; Chiao-Ting Chen; Jain-Wun Su; Ting-Yun Wang; Szu-Hao Huang; (2021). Deep Learning Model for House Price Prediction Using Heterogeneous Data Analysis Along With Joint Self-Attention Mechanism. IEEE Access, (), –. doi:10.1109/access.2021.3071306
- [3]. Maryam Heidari;Setareh Rafatirad; (2020). Semantic Convolutional Neural Network model for Safe Business Investment by Using BERT. 2020 Seventh International Conference on Social Networks Analysis, Management and Security (SNAMS), (), -. doi:10.1109/snams52053.2020.9336575
- [4]. Jain, Mansi; Rajput, Himani; Garg, Neha; Chawla, Pronika (2020). [IEEE 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC) - Coimbatore, India (2020.7.2-2020.7.4)] 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC) - Prediction of House Pricing using Machine Learning with Python., (), 570–574. doi:10.1109/ICESC48915.2020.9155839
- [5]. Truong, Quang; Nguyen, Minh; Dang, Hy; Mei, Bo (2020). Housing Price Prediction via Improved Machine Learning Techniques. Procedia Computer Science, 174(), 433–442. doi:10.1016/j.procs.2020.06.111
- [6]. Manasa, J; Gupta, Radha; Narahari, N S (2020). [IEEE 2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) - Bangalore, India (2020.3.5-2020.3.7)] 2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) - Machine Learning based Predicting House Prices using Regression Techniques., (), 624–630. doi:10.1109/ICIMIA48430.2020.9074952
- [7]. Madhuri, CH. Raga; Anuradha, G; Pujitha, M. Vani (2019). [IEEE 2019 International Conference on Smart Structures and Systems (ICSSS) Chennai, India (2019.3.14-2019.3.15)] 2019 International Conference on Smart Structures and Systems (ICSSS) House Price Prediction Using Regression Techniques: A Comparative Study., (), 1–5. doi:10.1109/ICSSS.2019.8882834
- [8]. Peng, Zhen; Huang, Qiang; Han, Yincheng (2019). [IEEE 2019 IEEE 11th International Conference on Advanced Infocomm Technology (ICAIT) Jinan, China (2019.10.18-2019.10.20)] 2019 IEEE 11th International Conference on Advanced Infocomm Technology (ICAIT) -

Model Research on Forecast of Second-Hand House Price in Chengdu Based on XGboost Algorithm. , (), 168-172. doi:10.1109/ICAIT.2019.8935894

- [9]. Jiang, Zhongyun; Shen, Guoxin (2019). [IEEE 2019 6th International Conference on Systems and Informatics (ICSAI) Shanghai, China (2019.11.2-2019.11.4)] 2019 6th International Conference on Systems and Informatics (ICSAI) Prediction of House Price Based on The Back Propagation Neural Network in The Keras Deep Learning Framework., (), 1408–1412. doi:10.1109/ICSAI48974.2019.9010071
- [10]. Varma, Ayush; Sarma, Abhijit; Doshi, Sagar; Nair, Rohini (2018). [IEEE 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT) - imbatore (2018.4.20-2018.4.21)] 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT) - House Price Prediction Using Machine Learning and Neural Networks., (), 1936–1939. doi:10.1109/ICICCT.2018.8473231