Age Group Estimation Model using K-Nearest Neighborhood

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Abstract: Age estimation labels exact real age or age group for a given face image. How to recognise the face of a human depends upon the age invariant features and patterns. After finding out the aging patterns, the researchers are in investigation to find out in what way we can characterise the aging of a face to get accurate performance. We can estimate the age through multi class classification or regression or a combination of both classification and regression. In our paper we are classifying, predicting and evaluating our proposed aging pattern algorithm to estimate the age. The brief process is first we split the data in to two subsets i.e training data and test data by using stratified cross validation method. By using training data and test data we are classifying or predicting the age group using K-neighbourhood method and evaluation measures are considered by using confusion matrix. The Classification and Evaluation of Age estimation models results us to find out the best estimation model for different types of datasets which are used in different applications like biometric, law enforcement, and security control and human-computer interaction.

Keywords: age estimation, K neighbourhood, multiclass confusion matrix, prediction, evaluation

I. INTRODUCTION

Collecting large databases of images is also a challenging task for estimation of Age. There is many methods to extract the key features from each database. Among them one of the current main stream method is which extract the face feature vectors directly from human face is Local Binary Pattern model. After extracting the face features from facial image the labelling of the age can be done by a class or by a set of sequential values. If the labelling is done through a class then it is solved through classification otherwise it is solved through regression .Identification of the face and recognition of the features also improves the human interaction of computer.

By using the evaluation protocol we can determine the test set, and what are the conditions to select the data for testing and can evaluate the performance of given model. To evaluate the age estimation cross validation is one method. It divides the data into two subsets .One subset is used to train or learn age estimation model and another subset is used to validate or evaluate the model. A stratified cross validation is used to improve the accuracy.

The age estimation can be done for our proposed algorithm by using classifier called KNN classifier and we are evaluating the performance of our algorithm by Accuracy, F1 score by calculating confusion matrix. The multi class classification considers the age value as a separate category. The rest of the paper is organized as follows: Section II describes some of the related works i.e. Literature Survey. Section III presents the proposed age estimation system. Experimental results and discussion are discussed in Section IV. Finally, concluding comments are provided in Section V.

II. LITERATURE SURVEY

A. Facial aging Different Databases

There are different types of facial aging databases. They are MORPH database, FG-NET aging database, Yamaha gender and age (YGA) database, WIT-DB database Burt’s Caucasian face database, LHI face database, HOP face database, Iranian face database, Gallagher’s web-collected database, Ni’s web-collected database, Kyaw’s web-collected database, BERC database, 3D morphable database. In our present research work we use some of the databases to implement our proposed algorithm.

B. Data Splitting methods

There are different data splitting methods. They are

a) Cross-Validation (CV)  b) Bootstrap and Monte-Carlo Cross-Validation (MCCV)

c) Bootstrapped Latin Partition (BLP) d) Kennard-Stone algorithm (K-S) and Sample Set Partitioning Based on Joint X–Y Distances Algorithm (SPXY)

Our present research work uses Stratified cross validation is used to split train dataset and test dataset .Here we discuss some different types of Cross Validation.

1) Leave One Out Cross Validations(LOOCV)

Among 100 data points records we are taking one data point as a dataset and the remaining all are as an training dataset. In this way we repeat the process 100 times by taking all different data points as an test set. The main drawback is this method having low bias and computationally expensive

2) k-fold cross-validation

In K-fold cross validation we have to assume k value preferable to select odd value. Suppose k=5 means we have to perform 5 experiments on our 100 dataset points. Now the no of data points in test data is 100/5=25 data points and the remaining data points are treated as training dataset .so this is repeated until all other 25 data points are selected as test data set .This type of splitting
may leads to imbalance dataset because all different types of categories may not include in k –fold test dataset.

3) Stratified Cross Validation

It is similar to K-fold cross validation. Only difference is select that 25 data points such that it covers all classes belong to our dataset points. Similarly we have to perform 5 experiments on our 100 dataset points by selecting different 25 dataset points which includes all different class type instances.

4) Time Series cross validation

In this we are predicting day5 data by considering the data from day1 to day4. Similarly we are predicting day6 data by considering the data from day2 to day5. In this way we will find out the new values.

C. Classification methods

Classification is one of the most commonly used techniques to classify the large records or datasets. The classification of the data involves learning to analyse the trained data to build a model and also involves estimating the accuracy of the model using test data. The established rules from the given model is applied on new dataset. Several algorithms are developed based on multi-class classification. Those are neural networks, decision trees, k-nearest neighbours, naive bayes, support vector machines and extreme learning machines. In our proposed research work we use KNN to classify and predict Multiclass categories.

1) k-nearest neighbours

we can perform classification by using KNN classifier as it is based on feature similarity. It is one of the simplest supervised machine learning algorithms mostly used for classifying a data point.

It classifies the data based on the way of the neighbour’s classification. It stores all available classes and new dataset points are classified based on similarity measure. k is a parameter that refers to the number of nearest neighbours we have consider. The k value should always be odd i.e., 3, 5, 7….Use formula k=Sqrt(n) where n is the total no of data points. Here we have to calculate the Euclidean distance from unknown data point to all known data points. Next we select k entries in our database which are closest to the unknown sample. Among them the most common classification gives us the solution.

D. The Confusion matrix for multiple classes

The confusion matrix is a matrix where columns represent the predicted classes and rows represent the actual classes. The diagonal values are True Positive values for their respective class. The confusion matrix is used to measure the model performance.

We are using Accuracy, Precision, Recall, F1 score are the performance measures based on confusion matrix. To select one of the models we have to use one of the performance measure based on the dataset points. To calculate those performance methods we have to know about the following terms

1) True Positive: True Positive (TP) are the values which are correctly identified for each class i.e. When both actual class of the data point and the predicted was true.

2) True Negatives: True Negatives (TN) are correctly rejected for a given class i.e. when both actual class of the data point and the predicted was false.

3) False Positives: False Positives (FP) are incorrectly identified for certain class i.e. when the actual class of the data point is false and predicted as true

4) False Negatives: False Negatives (FN) are incorrectly rejected for certain class i.e. when actual class of the data point was true and predicted as false.

The performance measures based on confusion matrix are

a. Accuracy: It is calculated as total no of correct predictions divided by total number of data points

\[ \text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \]

b. Precision: The output of the precision is it returns only relevant instances of a given model. The formula of the precision for a given class A is

\[ \text{Precision} = \frac{TP_A}{TP_A + FP_A} \]

So Average Precision=\(P(A) +P(B) +……..+P(N)/N \)

c. Recall or Sensitivity: The output of the sensitivity is to identify all relevant instances. The formula of the sensitivity for a given class A is

\[ \text{Recall} = \frac{TP_A}{TP_A + FN_A} \]

So Average Recall=\(R(A)+R(B)+…+R(N)/N \)

d. F1 score: The output of the F1 score is the harmonic mean of recall and precision. Single metric that combines recall and precision using the harmonic mean

\[ \text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \]

\[ \text{F1 Score} = \frac{2 \times \text{Recall}/(\text{Recall} + \text{Precision})}{\text{Recall}/(\text{Recall} + \text{Precision}) + (\text{Recall}/(\text{Recall} + \text{Precision}))} \]

E. Nth order Neighbourhood

The fig(1) illustrates different orders of neighbourhood for a central pixel. Most of the research involved in image processing is mostly revolved around second order neighbourhood only. This is because all the 8-neighbouring pixels are well connected with central pixels and the methods based on second order neighbourhood are given extraordinary results.
F. Local Binary Patterns

Local Binary Patterns technique. This method detects different kinds of patterns like spot, edges, lines flat areas which are on the skin. The LBP patterns of spot, edges, lines, and flat areas can be identified

![Fig 2. Example of LBP operation LBP techniques are used to describe textures](image)

like gender classification, age estimation, and facial component tracking. The process of LBP is shown in Fig2. The centre pixel value is treated as Threshold value. If the values are greater than the threshold value, then that value is converted as 1 otherwise it is converted as 0. Then the summation of all the values gives us a binary number. While summing the binary number with highest value gives us rotation invariant feature. The LBP operator is used to find out the features for different types of neighbourhood with different radii. The LBP codes are categorized as uniform and non-uniform patterns. Uniform patterns represent structures like line, spot, edge and flat area. The 2 bit wise transitions i.e. from 0 to 1 or 1 to 0 are categorized as uniform pattern. We say the pattern is a uniform pattern if transitions i.e. from 0 to 1 or 1 to 0 are categorized as uniform pattern. We say the pattern is a uniform pattern if transitions from 0 to 1 or 1 to 0 are counted as uniform transitions. The transition means value is changed either from one to zero or zero to one. The present research derives the algorithm for ‘<’ pattern and ‘>’ pattern in 5x5 window consists of 5 pixels. The 5x5 window is moved to overall image of size N x N such that 5x5 window covers each and every pixel. In the fig(4) ‘<’ pattern pixels are indicated with one colour and ‘>’ pixels are indicated with another colour. The positions c1, c2, c5, c10, c13 form ‘<’ pattern and the positions c1, c4, c9, c12, c13 form ‘>’ pattern.

![Fig(4) a)’<’ pattern b)’>’pattern](image)

G. Conversion of 5x5 neighbourhood into 3x3 neighbourhood and then to LBP code

We are converting 5x5 neighbourhood into 3x3 neighbourhood by finding out the mean of all the 4 middle values as shown in Fig(3). From the above figure we can say the top value is changed as 40 by finding mean of (30, 51). The bottom value is changed as 35 by finding out the mean of (38, 33).

![Fig(3) a) 5x5 neighbourhood b) 3x3 neighbourhood c) Binary form of LBP and its code](image)

The right value is changed as 39 by finding mean of (42, 6). The Left value is changed as 48 by finding out the mean of (57, 40). We can easily find out the LBP binary value ad LBP decimal value from third order neighbourhood

III. PROPOSED METHOD

A. Counting the zero, two, four transitions for Left Angle Pattern Count and Right Angle Pattern Count

1) First the image is converted into their corresponding pixel value. Each and every pixel in the image is then converted into LBP code as shown in the fig(5). Here we are using some of the facial database images as input.

2) Each image is divided into blocks of size N x N. Our present research derives the algorithm for ‘<’ pattern and ‘>’ pattern in 5x5 window consists of 5 pixels. The 5x5 window is moved to overall image of size N x N such that 5x5 window covers each and every pixel. In the fig(4) ‘<’ pattern pixels are indicated with one colour and ‘>’ pixels are indicated with another colour. The positions c1, c2, c5, c10, c13 form ‘<’ pattern and the positions c1, c4, c9, c12, c13 form ‘>’ pattern.

3) In each ‘<’ and ‘>’ patterns count the number of 0, 2, 4 transition in the pattern. The transition means value is changed either from one-to-zero or zero-to-one in pattern. The present paper considers the transitions in circularly. While considering the pattern circularly, three types of transitions are occurred i.e. 0, 2, and 4 transitions. For example, the considered pattern ‘00000’ or ‘11111’ has 0 transitions, while patterns ‘00001, 00010, and so on have two 1->0 or 0->1 transitions. The binary patterns like ‘00101, 01001, 01101 and other circularly pivoted bitwise turned renditions have 4 one-to-zero or zero-to-one transitions.
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The present approach uses 5 bits to form ‘<’ and inverted ‘>’ patterns of TNP. So, totally forms 32 distinct patterns with one of the 3 transitions i.e. zero, two and four transitions. The present approach evaluated the frequency occurrences of transitions on ‘<’ and ‘>’ of TNP on the facial images for estimating the age groups. Each ‘<’ or ‘>’ pattern consists of 5 bit pattern. The different combinations for 5 bit pattern are 2^5 i.e. 32 bit patterns. There are two 0 transitions for decimal values 0 and 31. The decimal values 5,9,10,11,13,18,20,21,22,26 results for 0 to 1 or 1 to 0 four transitions. The rest of the binary equivalent decimal values 1,2,3,4,6,7,8,12,14,15,16,17,19,23,24,25,27,28,29,30 results two transitions. For each image we can count how many number of zero, two, four no of transitions occurred for a given database easily from the above explained information.

| S. No | Image Name | Left-pattern Count (LAC) | Right-pattern Count (RAC) |
|-------|------------|--------------------------|----------------------------|
| 1     | 001602     | 140 1501 300 184 494 4005 | 254 493 1195 259 2088 1496 | 244 |
| 2     | 001603     | 273 1010 959 1331 3321 896 | 254 493 1195 259 2088 1496 | 244 |
| 3     | 001604     | 421 1020 900 1441 2120 325 | 254 493 1195 259 2088 1496 | 244 |
| 4     | 001605     | 561 1280 600 1741 3081 1895 | 254 493 1195 259 2088 1496 | 244 |
| 5     | 001606     | 250 1241 570 1771 3181 2541 | 254 493 1195 259 2088 1496 | 244 |
| 6     | 001607     | 750 1550 1500 2042 3250 2541 | 254 493 1195 259 2088 1496 | 244 |
| 7     | 001608     | 255 399 816 1525 1351 3806 | 254 493 1195 259 2088 1496 | 244 |
| 8     | 001609     | 558 1550 353 2058 841 3803 | 254 493 1195 259 2088 1496 | 244 |
| 9     | 001610     | 558 1550 353 2058 841 3803 | 254 493 1195 259 2088 1496 | 244 |
| 10    | 001611     | 557 1000 704 1627 1321 2764 | 2541 493 1195 259 2088 1496 | 244 |
| 11    | gi008      | 566 1220 375 1766 1341 1775 | 254 493 1195 259 2088 1496 | 244 |
| 12    | gi005      | 768 385 900 1441 1478 1765 | 254 493 1195 259 2088 1496 | 244 |
| 13    | gi002      | 571 1100 670 1859 1391 1953 | 254 493 1195 259 2088 1496 | 244 |
| 14    | gi009      | 594 1550 197 2144 971 1747 | 254 493 1195 259 2088 1496 | 244 |
| 15    | gi007      | 553 1370 340 5003 971 1710 | 254 493 1195 259 2088 1496 | 244 |
| 16    | gi006      | 658 1550 394 2145 932 5705 | 254 493 1195 259 2088 1496 | 244 |
| 17    | gi005      | 670 1121 540 1801 1220 8371 | 2541 493 1195 259 2088 1496 | 244 |
| 18    | gi009      | 685 1484 222 3553 2198 8561 | 254 493 1195 259 2088 1496 | 244 |
| 19    | gi007      | 700 1490 181 2160 981 3641 | 254 493 1195 259 2088 1496 | 244 |
| 20    | gi005      | 705 1430 181 2160 981 3641 | 254 493 1195 259 2088 1496 | 244 |

Example Table1. Frequency occurrences of transition ‘<’ and ‘>’ patterns of TNP for childhood images

B) Derived Algorithm to estimate the Age

From the data in FV tables, define a user defined algorithm for estimating the age group of the input facial test image. The algorithm classify the facial test input image into one of the pre- defined class group such as Childhood (0-12 years), Young Adults (13-25 years), Middle-aged Adults (26-40 years), Senior Adults (40-60 years) and Senior Citizens (more than 60 years). The derived user defined algorithm is defined in algorithm1.

Algorithm 1: Age group estimation (image)

Input: facial test image for Age group estimation
Output: Age group

Start
Step 1: Extract the skin region of the face using HIS model
Step 2: Crop the Skin region of the facial image.
Step 3: Convert the Crop color image into grey level image by using HIS color model
Step 4: Convert each 5x5 sub image of TNP into two valued matrix
Step 5: find transition trends of ‘<’ and ‘>’ patterns in each 5x5 sub image of TNP.
Step 6: Based on the transition count, estimate the age group of the test image. Let LAC be ‘<’ pattern count, RAC be the ‘>’ pattern count, 0 be the zero transition count, 2 be the two transition count, 4 be the four transition count.

Fig(5) Input image Output image
If ((LAC (0) <= 734) and (RAC (0+4 > 1143)) && (RAC (0+4 < 1269))

Print ("Facial image is considered as Childhood aged group");
Else if ((LAC (0) < 837) and (RAC (0+4 > 1269) && (RAC (0+4 < 1494))

Print ("Facial image is considered as Young adult aged group");
Else if ((LAC (0) < 909) and (RAC (0+4 > 1049) && (RAC (0+4 < 1086))

Print ("Facial image is considered as middle aged group");
Else if ((LAC (0) < 1013) and (RAC (0+4 < 1049))

Print ("Facial image is considered as Senior aged Group");
Else if ((LAC (0) < 1193) and (RAC (0+4 > 1085) && (RAC (0+4 < 1143))

Print ("Facial image is considered as Senior Citizen aged Group");
Else

Print ("Unknown age group");
End

7) Now we have to test the performance of algorithm by using KNN classifier and we use performance measures like Accuracy and F1 score to determine how best our model is
a. The KNN classifier must have one training data set and one test dataset to classify the data and to predict the data.
b. In our research work to divide the data into training dataset and test dataset we are using stratified cross validation method
c. Stratified Cross Validation: It is similar to K-fold cross validation. In this method we select the test set such that it includes all types of instances so that we can get more accuracy rate for our derived model. This method splits the data into Train dataset and Test dataset which is taken from 5 different databases as shown in results and experiments.
d. Now the KNN classifier classifies new data or predicts the data by finding out the 3 nearer values for each and every training dataset using Euclidean distance. Among the 3 values we consider the age group category in which two values represents the more or max values representation.
e. At last we find the performance of our algorithm with Accuracy and F1 score using confusion matrix.

IV. RESULTS AND EXPERIMENTS

Table 2. shows us the Euclidean distance for each and every test data set

| Lac(0) | Rac(0+4) | Age group | ED1   | ED2   | ED3   | ED4   | ED5   | ED6   | ED7   | ED8   | ED9   | ED10  |
|--------|----------|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 557    | 1209     | 1         | 97.493| 182.14| 187.87| 314.54| 324.99| 364.47| 486.78| 478.7  | 484.14| 638.52|
| 566    | 1210     | 1         | 106.53| 173.29| 179.07| 306.47| 317.65| 356.39| 480.93| 470.62 | 475.71| 629.68|
| 781    | 1330     | 2         | 349.68| 81.835| 74.652| 64.031| 285.37| 273.73| 471.84| 364.68 | 345.77| 451.95|
| 796    | 1333     | 2         | 363.46| 94.047| 86.977| 53.235| 285.56| 270.38| 470.77| 358.05 | 337.55| 439.65|
| 870    | 1075     | 3         | 425.4 | 236.81| 239.38| 308.91| 37.643| 202.61| 139.71| 155.32 | 328.89|
| 872    | 1077     | 3         | 426.78| 236.4 | 238.89| 307.26| 40.459| 27.658| 204.15 | 138.24 | 153.2 | 326.53|
| 945    | 998      | 4         | 521.43| 343.58| 345.82| 401.62| 116.72| 96.648| 75.802| 118.19 | 285.91|
| 952    | 1009     | 4         | 523.99| 339.6 | 341.6 | 393.44| 91.021| 137.64| 63.812| 105.38 | 274.38|
| 1092   | 1115     | 5         | 635.68| 392.23| 390.91| 379.03| 259.03| 195.63| 297.8  | 138.84 | 73.409| 103.58|
| 1124   | 1122     | 5         | 666.58| 419.14| 417.49| 397.31| 292.01| 228.52| 324.09 | 142.56 | 105.68| 70.88 |
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Table 3 The Training dataset which is taken from 5 different databases is shown in the below

| LAC(0) | RAC(0+4) | AGE GROUP |
|--------|----------|-----------|
| 557    | 1209     | childhood |
| 566    | 1210     | childhood |
| 781    | 1330     | young     |
| 796    | 1333     | young     |
| 870    | 1075     | middle    |
| 872    | 1077     | middle    |
| 945    | 998      | senior age|
| 952    | 1009     | senior age|
| 1092   | 1115     | Senior citizens |
| 1124   | 1122     | Senior citizens |

Training Dataset

Table 4 The Test dataset which is taken from 5 different databases is shown in the below

| LAC(0) | RAC(0+4) | Age Group |
|--------|----------|-----------|
| 461    | 1192     | child     |
| 730    | 1266     | child     |
| 734    | 1272     | young     |
| 821    | 1380     | young     |
| 841    | 1051     | Middle    |
| 899    | 1083     | Middle    |
| 913    | 877      | Senior    |
| 1006   | 1043     | Senior    |
| 1025   | 1085     | Senior Citizen |
| 1192   | 1142     | Senior Citizen |

Test dataset

**Step1.** The Table 3 and Table 4 are Training data set and test dataset which are formed due to stratified cross validation.

**Step2.** The Table 2 results are obtained after using KNN classifier with k=3 and distance measure is taken as Euclidean distance.

For Example: If Lac(0)=461 and Rac (0+4)=1192 then predict the Age Group?.

Sol:- From the above table by using KNN with k=3 ,we find the Euclidean distance (ED1) for all the training dataset ,the first three shortest distance values will give you the result. Among them two shortest distance value results to Age Group category -1 i.e. Child and one shortest distance results to Age Group category-2, Young. At last we decide the result as CHILD AGE GROUP. In this way we predict the Age group of all Test Data set.

**Step3.** By using the KNN we build the above table2 and using that table we construct confusion Matrix table5 and find the performance metrics like Accuracy, F1 score to identify the performance of our Algorithm. This is a Multi class Confusion Matrix. i.e... the matrix which is having more than 2 classes. In this confusion matrix there are 5 different classes. The diagonal values of each and every class is treated True positive value (TP). Above the diagonal values and below the diagonal values are treated as False Positive values (FP). Similarly The right and left of the diagonal values are treated as False Negative Values (FN). Similarly all the four corners of diagonal values are treated as True Negative Values (TN). By using TP, FP, FN, TN we can find out the Accuracy and F1 score algorithm for our proposed algorithm.

From the above figure we have to understood the Terms TP, TN, FP, FN. Mainly we have to consider the TP cell. The vertical values of TP represents False Positive values. The horizontal values of TP represent False Negative values. All the four corner values represent True Negative values.

**Multi Class Confusion Matrix**

| Age Group | Child | Young | Mid Age | Senior | Senior Citizen |
|-----------|-------|-------|---------|--------|----------------|
| Total     | 1     | 3     | 2       | 2      | 2              |

\[
TP = 1; \quad TP = 2; \quad TP = 2; \quad TP = 2
\]

\[
FP = 0; \quad FP = 1; \quad FP = 0; \quad FP = 0
\]

\[
P(1) = 1; \quad P(2) = 0.666; P(3) = 1; P(4) = 1; P(5) = 1
\]

**Step4. Different Performance Measures**

1) ACCURACY: For balanced data accuracy gives good results. If accuracy is high our model is good. But finding out the accuracy for imbalanced data misleads performance. The TP gives us correct classifications.

\[
\text{Accuracy} = \frac{TP1 + TP2 + TP3 + TP4 + TP5}{\text{Total no of Classifications}} = \frac{1 + 2 + 2 + 2 + 2}{10} = 0.9
\]
2) PRECISION:

Precision (Class 1) = P(1) = TP1/(TP1 + FP1)
P(1) = 1/1+0 = 1;  P(2) = 2/2+1 = 2/3 = 0.666;
P(3) = 2/2+0 = 1;  P(4) = 2/2 = 1;
P(5) = 2/2 = 1;
So Average Precision = (1 + 0.666 + 1 + 1 + 1)/5 = 0.9332

3) RECALL:

Recall(Class 1) = R(1) = TP1/(TP1 + FN1)
R(1) = 1/1+1 = 0.5;  R(2) = 2/2+0 = 1; R(3) = 2/2 = 1;
R(4) = 2/2 = 1; R(5) = 2/2 = 1; So Average Recall = (0.5 + 1 + 1 + 1 + 1)/5 = 0.9

4) F1 SCORE:

F1 score = 2 * Precision * Recall / (Precision + Recall) = 2 * 0.9332 * 0.9/(0.9332 + 0.9); = 1.67976/1.832 = 0.916899

V. CONCLUSION

The present paper evaluates the performance of our derived algorithm from Left angular pattern count and Right angular pattern count. The K-nearest neighbour classifier classifies the data and predicts the dataset. The accuracy of our proposed derived algorithm is 0.9. The F1 score value for our proposed algorithm is 0.916899. The accuracy value for our model is good when the dataset in confusion matrix is balanced data. For imbalanced data the F1 score is the perfect measure. In Future for our derived model we can use some other classifiers like naive bayes, neural networks. In the same way we can use other metrics to measure the performance.

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