fitcdiscr

Fit discriminant analysis classifier

Syntax

```
Mdl = fitcdiscr(Tbl,ResponseVarName)
Mdl = fitcdiscr(Tbl,formula)
Mdl = fitcdiscr(Tbl,Y)

Mdl = fitcdiscr(X,Y)

Mdl = fitcdiscr( __ ,Name=Value)
[Mdl,AggregateOptimizationResults] = fitcdiscr( __ )
```

Description

`Mdl = fitcdiscr(Tbl,ResponseVarName)` returns a fitted discriminant analysis model based on the input variables (also known as predictors, features, or attributes) contained in the table `Tbl` and output (response or labels) contained in `ResponseVarName`.

`Mdl = fitcdiscr(Tbl,formula)` returns a fitted discriminant analysis model based on the input variables contained in the table `Tbl`. `formula` is an explanatory model of the response and a subset of predictor variables in `Tbl` used to fit `Mdl`.

`Mdl = fitcdiscr(Tbl,Y)` returns a fitted discriminant analysis model based on the input variables contained in the table `Tbl` and response `Y`.

`Mdl = fitcdiscr(X,Y)` returns a discriminant analysis classifier based on the input variables `X` and response `Y`. example

`Mdl = fitcdiscr( __ ,Name=Value)` fits a classifier with additional options specified by one or more name-value arguments, using any of the previous syntaxes. For example, you can optimize hyperparameters to minimize the model's cross-validation loss, or specify the cost of misclassification, the prior probabilities for each class, or the observation weights. example

`[Mdl,AggregateOptimizationResults] = fitcdiscr( __ )` also returns `AggregateOptimizationResults`, which contains hyperparameter optimization results when you specify the `OptimizeHyperparameters` and `HyperparameterOptimizationOptions` name-value arguments. You must also specify the `ConstraintType` and `ConstraintBounds` options of `HyperparameterOptimizationOptions`. You can use this syntax to optimize on compact model size instead of cross-validation loss, and to perform a set of multiple optimization problems that have the same options but different constraint bounds.

Note

For a list of supported syntaxes when the input variables are tall arrays, see Tall Arrays.

Examples

collapse all

Train Discriminant Analysis Model

Load Fisher's iris data set.

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Copy Command

```
load fisheriris
```

Train a discriminant analysis model using the entire data set.

```
Mdl = fitcdiscr(meas,species)
```

```
Mdl = 
  ClassificationDiscriminant
           ResponseName: 'Y'
    CategoricalPredictors: []
             ClassNames: {'setosa'  'versicolor'  'virginica'}
         ScoreTransform: 'none'
        NumObservations: 150
            DiscrimType: 'linear'
                     Mu: [3×4 double]
                 Coeffs: [3×3 struct]


  Properties, Methods
```

`Mdl` is a `ClassificationDiscriminant` model. To access its properties, use dot notation. For example, display the group means for each predictor.

```
Mdl.Mu
```

```
ans = 3×4

    5.0060    3.4280    1.4620    0.2460
    5.9360    2.7700    4.2600    1.3260
    6.5880    2.9740    5.5520    2.0260
```

To predict labels for new observations, pass `Mdl` and predictor data to `predict`.

Optimize Discriminant Analysis Model

This example shows how to optimize hyperparameters automatically using `fitcdiscr`. The example uses Fisher's iris data.

Load the data.

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```
load fisheriris
```

Find hyperparameters that minimize five-fold cross-validation loss by using automatic hyperparameter optimization.

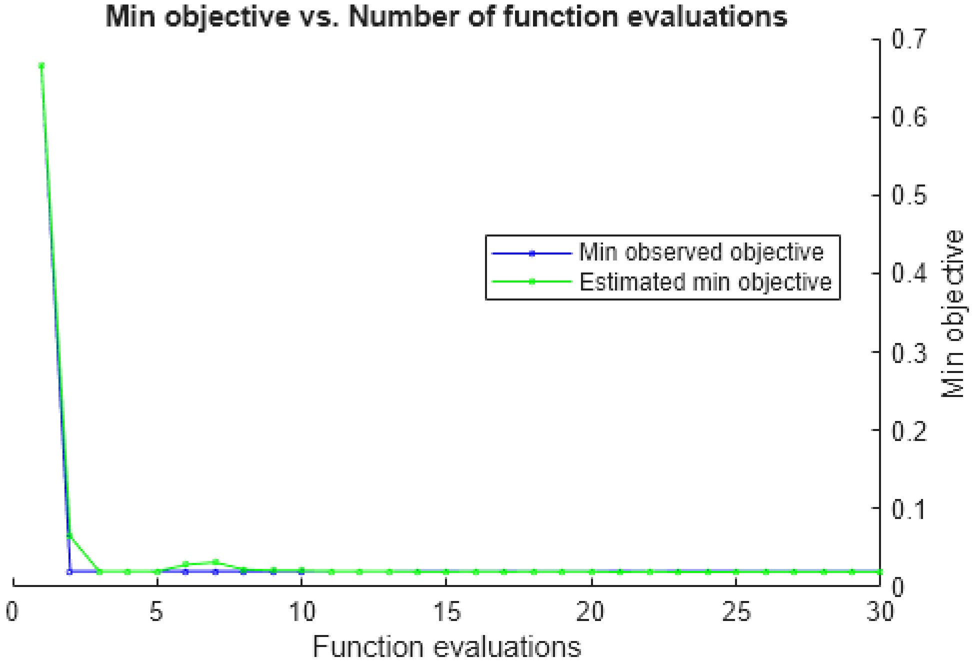
For reproducibility, set the random seed and use the `'expected-improvement-plus'` acquisition function.

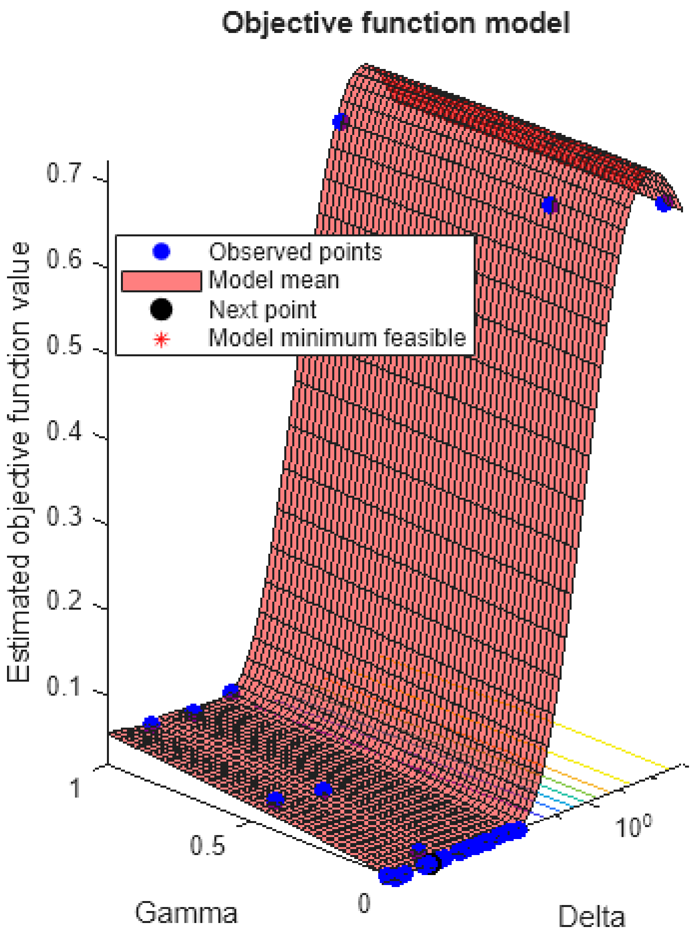
```
rng(1)
Mdl = fitcdiscr(meas,species,'OptimizeHyperparameters','auto',...
    'HyperparameterOptimizationOptions',...
    struct('AcquisitionFunctionName','expected-improvement-plus'))
```

Get

```
|=====================================================================================================
| Iter | Eval   | Objective   | Objective   | BestSoFar   | BestSoFar   |        Delta |
|      | result |             | runtime     | (observed)  | (estim.)    |              |
|=====================================================================================================
|    1 | Best   |     0.66667 |      0.5599 |     0.66667 |     0.66667 |       13.261 |
|    2 | Best   |        0.02 |     0.20361 |        0.02 |    0.064227 |   2.7404e-05 |     0
|    3 | Accept |        0.04 |      0.1408 |        0.02 |    0.020084 |   3.2455e-06 |
|    4 | Accept |     0.66667 |     0.05779 |        0.02 |    0.020118 |       14.879 |
|    5 | Accept |    0.046667 |    0.041831 |        0.02 |    0.019907 |   0.00031449 |
|    6 | Accept |        0.04 |    0.037865 |        0.02 |    0.028438 |   4.5092e-05 |
|    7 | Accept |    0.046667 |    0.063158 |        0.02 |    0.031424 |   2.0973e-05 |
|    8 | Accept |        0.02 |    0.035232 |        0.02 |    0.022424 |   1.0554e-06 |    0.
|    9 | Accept |        0.02 |    0.037108 |        0.02 |    0.021105 |   1.1232e-06 |   0.0
|   10 | Accept |        0.02 |    0.042567 |        0.02 |    0.020948 |   0.00011837 |    0.
|   11 | Accept |        0.02 |     0.03459 |        0.02 |    0.020172 |   1.0292e-06 |     0
|   12 | Accept |        0.02 |    0.055514 |        0.02 |    0.020105 |   9.7792e-05 |    0.
|   13 | Accept |        0.02 |    0.045267 |        0.02 |    0.020038 |   0.00036014 |    0.
|   14 | Accept |        0.02 |    0.033937 |        0.02 |    0.019597 |   0.00021059 |    0.
|   15 | Accept |        0.02 |    0.070328 |        0.02 |    0.019461 |   1.1911e-05 |    0.
|   16 | Accept |        0.02 |    0.081124 |        0.02 |     0.01993 |    0.0017896 |   0.0
|   17 | Accept |        0.02 |    0.039471 |        0.02 |    0.019551 |   0.00073745 |    0.
|   18 | Accept |        0.02 |    0.078447 |        0.02 |    0.019776 |   0.00079304 |   0.0
|   19 | Accept |        0.02 |    0.049007 |        0.02 |    0.019678 |     0.007292 |    0.
|   20 | Accept |    0.046667 |    0.041023 |        0.02 |    0.019785 |    0.0074408 |
|=====================================================================================================
| Iter | Eval   | Objective   | Objective   | BestSoFar   | BestSoFar   |        Delta |
|      | result |             | runtime     | (observed)  | (estim.)    |              |
|=====================================================================================================
|   21 | Accept |        0.02 |    0.043131 |        0.02 |    0.019043 |    0.0036004 |    0.
|   22 | Accept |        0.02 |    0.043938 |        0.02 |    0.019755 |   2.5238e-05 |    0.
|   23 | Accept |        0.02 |     0.09227 |        0.02 |      0.0191 |   1.5478e-05 |    0.
|   24 | Accept |        0.02 |    0.034113 |        0.02 |    0.019081 |    0.0040557 |   0.0
|   25 | Accept |        0.02 |    0.032803 |        0.02 |    0.019333 |    2.959e-05 |    0.
|   26 | Accept |        0.02 |    0.050408 |        0.02 |    0.019369 |   2.3111e-06 |    0.
|   27 | Accept |        0.02 |    0.051046 |        0.02 |    0.019455 |   3.8898e-05 |    0.
|   28 | Accept |        0.02 |    0.040651 |        0.02 |    0.019449 |    0.0035925 |    0.
|   29 | Accept |     0.66667 |    0.043473 |        0.02 |    0.019479 |       998.93 |     0
|   30 | Accept |        0.02 |     0.05672 |        0.02 |     0.01947 |   8.1557e-06 |    0.

__________________________________________________________
Optimization completed.
MaxObjectiveEvaluations of 30 reached.
Total function evaluations: 30
Total elapsed time: 21.161 seconds
Total objective function evaluation time: 2.2371

Best observed feasible point:
      Delta         Gamma
    __________    ________

    2.7404e-05    0.073264
```

```
Observed objective function value = 0.02
Estimated objective function value = 0.022693
Function evaluation time = 0.20361

Best estimated feasible point (according to models):
      Delta         Gamma
    __________    _________

    2.5238e-05    0.0015542

Estimated objective function value = 0.01947
Estimated function evaluation time = 0.05596
```






```
Mdl = 
  ClassificationDiscriminant
                         ResponseName: 'Y'
                CategoricalPredictors: []
                           ClassNames: {'setosa'  'versicolor'  'virginica'}
                       ScoreTransform: 'none'
                      NumObservations: 150
    HyperparameterOptimizationResults: [1×1 BayesianOptimization]
                          DiscrimType: 'linear'
                                   Mu: [3×4 double]
                               Coeffs: [3×3 struct]


  Properties, Methods
```

The fit achieves about 2% loss for the default 5-fold cross validation.

Optimize Discriminant Analysis Model on Tall Array

This example shows how to optimize hyperparameters of a discriminant analysis model automatically using a tall array. The sample data set `airlinesmall.csv` is a large data set that contains a tabular file of airline flight data. This example creates a tall table containing the data and uses it to run the optimization procedure.

When you perform calculations on tall arrays, MATLAB® uses either a parallel pool (default if you have Parallel Computing Toolbox™) or the local MATLAB

This example uses:
Statistics and Machine Learning Toolbox
Parallel Computing Toolbox

session. If you want to run the example using the local MATLAB session when you have Parallel Computing Toolbox, you can change the global execution environment by using the `mapreducer` function.

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Create a datastore that references the folder location with the data. Select a subset of the variables to work with, and treat `NA` values as missing data so that `datastore` replaces them with `NaN` values. Create a tall table that contains the data in the datastore.

```
ds = datastore("airlinesmall.csv");
ds.SelectedVariableNames = ["Month","DayofMonth","DayOfWeek", ...
                            "DepTime","ArrDelay","Distance","DepDelay"];
ds.TreatAsMissing = "NA";
tt  = tall(ds) % Tall table
```

Get

```
Starting parallel pool (parpool) using the 'Processes' profile ...
07-Dec-2023 09:05:49: Job Queued. Waiting for parallel pool job with ID 1 to start ...
07-Dec-2023 09:06:50: Job Queued. Waiting for parallel pool job with ID 1 to start ...
Connected to parallel pool with 6 workers.

tt =

  M×7 tall table

    Month    DayofMonth    DayOfWeek    DepTime    ArrDelay    Distance    DepDelay
    _____    __________    _________    _______    ________    ________    ________

     10          21            3          642          8         308          12
     10          26            1         1021          8         296           1
     10          23            5         2055         21         480          20
     10          23            5         1332         13         296          12
     10          22            4          629          4         373          -1
     10          28            3         1446         59         308          63
     10           8            4          928          3         447          -2
     10          10            6          859         11         954          -1
      :          :             :           :          :           :           :
      :          :             :           :          :           :           :
```

Determine the flights that are late by 10 minutes or more by defining a logical variable that is true for a late flight. This variable contains the class labels. A preview of this variable includes the first few rows.

```
Y = tt.DepDelay > 10 % Class labels
```

Get

```
Y =

  M×1 tall logical array

   1
   0
   1
   1
   0
   1
   0
   0
   :
   :
```

Create a tall array for the predictor data.

```
X = tt{:,1:end-1} % Predictor data
```

```
X =

  M×6 tall double matrix

          10          21           3         642           8         308
          10          26           1        1021           8         296
          10          23           5        2055          21         480
          10          23           5        1332          13         296
          10          22           4         629           4         373
          10          28           3        1446          59         308
          10           8           4         928           3         447
          10          10           6         859          11         954
           :           :           :           :           :           :
           :           :           :           :           :           :
```

Remove rows in `X` and `Y` that contain missing data.

```
R = rmmissing([X Y]); % Data with missing entries removed
X = R(:,1:end-1);
Y = R(:,end);
```

Standardize the predictor variables.

```
Z = zscore(X);
```

Optimize hyperparameters automatically using the `OptimizeHyperparameters` name-value argument. Note that when you use tall arrays, `DiscrimType` is the only hyperparameter you can optimize, regardless of whether you specify `"auto"` or `"all"`. Find the optimal `DiscrimType` value that minimizes holdout cross-validation loss. For reproducibility, use the `"expected-improvement-plus"` acquisition function and set the seeds of the random number generators using `rng` and `tallrng`. The results can vary depending on the number of workers and the execution environment for the tall arrays. For details, see Control Where Your Code Runs.

```
rng("default")
tallrng("default")
[Mdl,FitInfo,HyperparameterOptimizationResults] = fitcdiscr(Z,Y, ...
    "OptimizeHyperparameters","auto", ...
    "HyperparameterOptimizationOptions",struct("Holdout",0.3, ...
    "AcquisitionFunctionName","expected-improvement-plus"))
```

```
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 2: Completed in 7.3 sec
- Pass 2 of 2: Completed in 3.8 sec
Evaluation completed in 19 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 4 sec
Evaluation completed in 4.3 sec
|=====================================================================================|
| Iter | Eval   | Objective   | Objective   | BestSoFar   | BestSoFar   |  DiscrimType |
|      | result |             | runtime     | (observed)  | (estim.)    |              |
|=====================================================================================|
|    1 | Best   |     0.11354 |      27.449 |     0.11354 |     0.11354 |    quadratic |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1.3 sec
Evaluation completed in 2.5 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1 sec
```

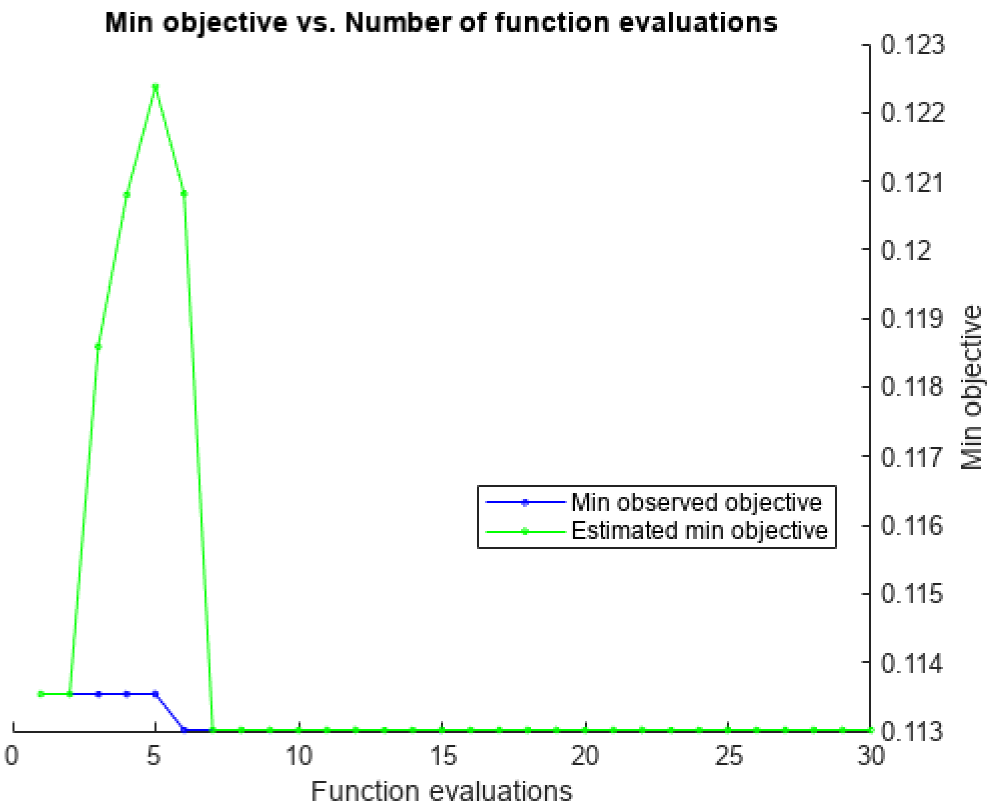
```
Evaluation completed in 1.2 sec
|    2 | Accept |     0.11354 |      5.4566 |     0.11354 |     0.11354 | pseudoQuadra |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.96 sec
Evaluation completed in 2.2 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.89 sec
Evaluation completed in 1.1 sec
|    3 | Accept |     0.12869 |      4.8549 |     0.11354 |     0.11859 | pseudoLinear |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.99 sec
Evaluation completed in 1.9 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.89 sec
Evaluation completed in 1.1 sec
|    4 | Accept |     0.12745 |      4.2867 |     0.11354 |      0.1208 |   diagLinear |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.98 sec
Evaluation completed in 2 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.84 sec
Evaluation completed in 1 sec
|    5 | Accept |     0.12869 |      4.6497 |     0.11354 |     0.12238 |       linear |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1 sec
Evaluation completed in 1.7 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.89 sec
Evaluation completed in 1.1 sec
|    6 | Best   |     0.11301 |      4.0594 |     0.11301 |     0.12082 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.96 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.82 sec
Evaluation completed in 1 sec
|    7 | Accept |     0.11301 |      4.0419 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.85 sec
Evaluation completed in 1 sec
|    8 | Accept |     0.11301 |      4.0382 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.97 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.81 sec
Evaluation completed in 1 sec
|    9 | Accept |     0.11301 |      3.9186 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1 sec
Evaluation completed in 1.9 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.84 sec
```

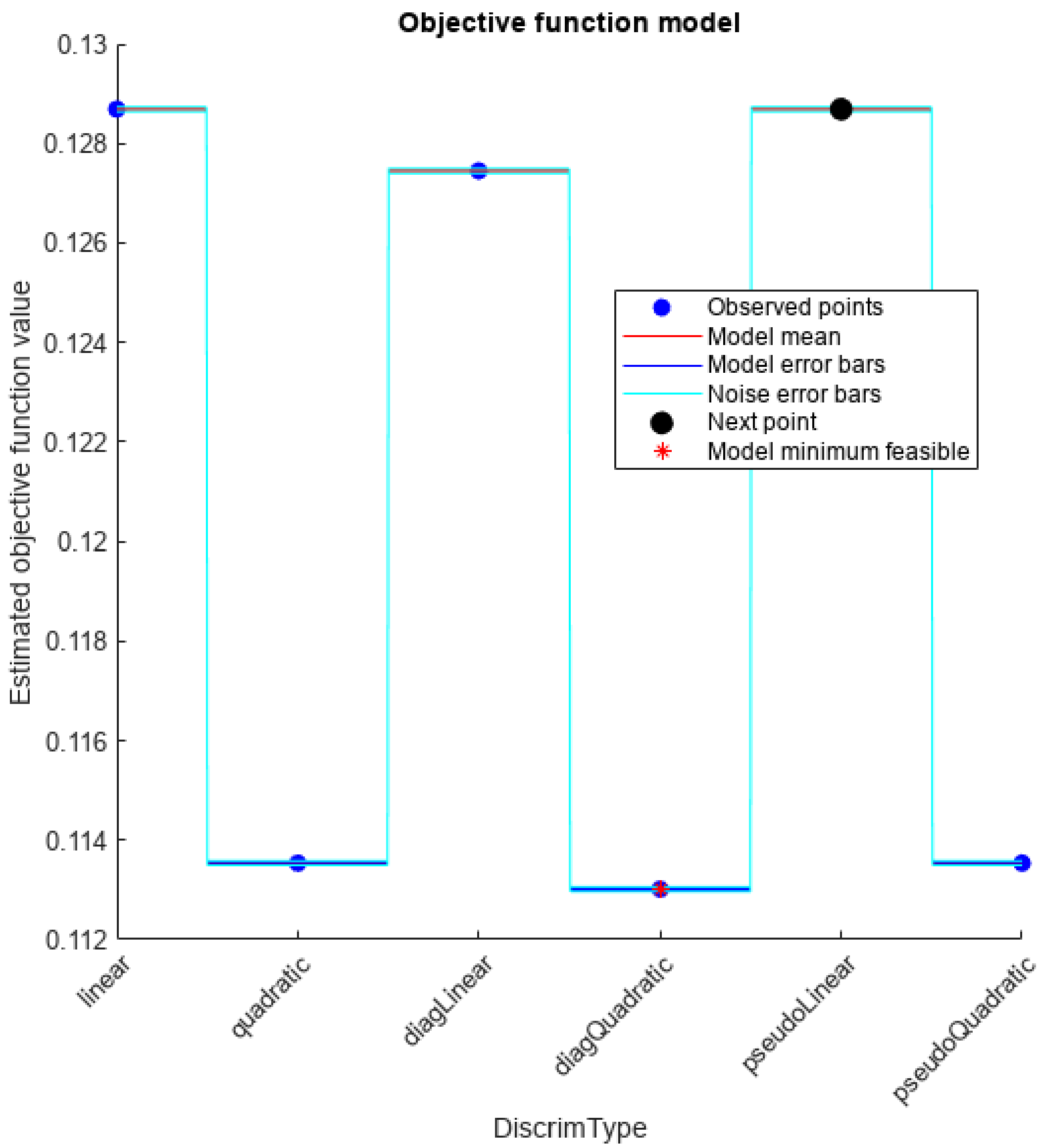
```
Evaluation completed in 1 sec
|   10 | Accept |     0.11301 |      4.0947 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1 sec
Evaluation completed in 1.9 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.88 sec
Evaluation completed in 1.1 sec
|   11 | Accept |     0.11301 |      4.3088 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.94 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.8 sec
Evaluation completed in 1 sec
|   12 | Accept |     0.11301 |      3.9644 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.86 sec
Evaluation completed in 1.1 sec
|   13 | Accept |     0.11301 |      4.0673 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.93 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.94 sec
Evaluation completed in 1.2 sec
|   14 | Accept |     0.11301 |      4.1285 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1.2 sec
Evaluation completed in 2 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.93 sec
Evaluation completed in 1.1 sec
|   15 | Accept |     0.11301 |      4.4217 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.98 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.89 sec
Evaluation completed in 1.1 sec
|   16 | Accept |     0.11301 |      4.0631 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.99 sec
Evaluation completed in 1.7 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.86 sec
Evaluation completed in 1.1 sec
|   17 | Accept |     0.11301 |      4.0227 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1 sec
Evaluation completed in 1.9 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.88 sec
```

```
Evaluation completed in 1.1 sec
|   18 | Accept |     0.11354 |      4.3391 |     0.11301 |     0.11301 | pseudoQuadra |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.98 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.85 sec
Evaluation completed in 1 sec
|   19 | Accept |     0.11301 |       4.139 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.97 sec
Evaluation completed in 1.9 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.91 sec
Evaluation completed in 1.1 sec
|   20 | Accept |     0.11301 |      4.2078 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1 sec
Evaluation completed in 1.9 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.86 sec
Evaluation completed in 1.1 sec
|=====================================================================================|
| Iter | Eval   | Objective   | Objective   | BestSoFar   | BestSoFar   |  DiscrimType |
|      | result |             | runtime     | (observed)  | (estim.)    |              |
|=====================================================================================|
|   21 | Accept |     0.11301 |      4.1129 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1.1 sec
Evaluation completed in 1.9 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.86 sec
Evaluation completed in 1.1 sec
|   22 | Accept |     0.11354 |      4.2473 |     0.11301 |     0.11301 |    quadratic |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.98 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.87 sec
Evaluation completed in 1.1 sec
|   23 | Accept |     0.11301 |      4.0342 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1.1 sec
Evaluation completed in 1.9 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.88 sec
Evaluation completed in 1.1 sec
|   24 | Accept |     0.11354 |       4.173 |     0.11301 |     0.11301 | pseudoQuadra |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.99 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.82 sec
Evaluation completed in 1.1 sec
|   25 | Accept |     0.11301 |      3.9707 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
```

```
- Pass 1 of 1: Completed in 1 sec
Evaluation completed in 1.7 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.98 sec
Evaluation completed in 1.2 sec
|   26 | Accept |     0.11354 |      4.1135 |     0.11301 |     0.11301 |    quadratic |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 1.1 sec
Evaluation completed in 2 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.92 sec
Evaluation completed in 1.1 sec
|   27 | Accept |     0.11301 |      4.2567 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.94 sec
Evaluation completed in 1.5 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.88 sec
Evaluation completed in 1.1 sec
|   28 | Accept |     0.11301 |      3.7988 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.97 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.88 sec
Evaluation completed in 1.1 sec
|   29 | Accept |     0.11301 |      3.9926 |     0.11301 |     0.11301 | diagQuadrati |
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.95 sec
Evaluation completed in 1.8 sec
Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.85 sec
Evaluation completed in 1 sec
|   30 | Accept |     0.11301 |      3.9793 |     0.11301 |     0.11301 | diagQuadrati |

__________________________________________________________
Optimization completed.
MaxObjectiveEvaluations of 30 reached.
Total function evaluations: 30
Total elapsed time: 180.1662 seconds
Total objective function evaluation time: 149.1907

Best observed feasible point:
     DiscrimType
    _____________

    diagQuadratic

Observed objective function value = 0.11301
Estimated objective function value = 0.11301
Function evaluation time = 4.0594

Best estimated feasible point (according to models):
     DiscrimType
    _____________
```

```
    diagQuadratic

Estimated objective function value = 0.11301
Estimated function evaluation time = 4.1702

Evaluating tall expression using the Parallel Pool 'Processes':
- Pass 1 of 1: Completed in 0.8 sec
Evaluation completed in 1.6 sec
```






```
Mdl = 
  CompactClassificationDiscriminant
           PredictorNames: {'x1'  'x2'  'x3'  'x4'  'x5'  'x6'}
             ResponseName: 'Y'
    CategoricalPredictors: []
               ClassNames: [0 1]
           ScoreTransform: 'none'
              DiscrimType: 'diagQuadratic'
                       Mu: [2×6 double]
                   Coeffs: [2×2 struct]


  Properties, Methods

FitInfo = struct with no fields.


HyperparameterOptimizationResults = 
  BayesianOptimization with properties:

                      ObjectiveFcn: @createObjFcn/tallObjFcn
              VariableDescriptions: [1×1 optimizableVariable]
                           Options: [1×1 struct]
```

```
                   MinObjective: 0.1130
               XAtMinObjective: [1×1 table]
         MinEstimatedObjective: 0.1130
      XAtMinEstimatedObjective: [1×1 table]
        NumObjectiveEvaluations: 30
               TotalElapsedTime: 180.1662
                      NextPoint: [1×1 table]
                         XTrace: [30×1 table]
                 ObjectiveTrace: [30×1 double]
               ConstraintsTrace: []
                  UserDataTrace: {30×1 cell}
   ObjectiveEvaluationTimeTrace: [30×1 double]
             IterationTimeTrace: [30×1 double]
                     ErrorTrace: [30×1 double]
               FeasibilityTrace: [30×1 logical]
    FeasibilityProbabilityTrace: [30×1 double]
            IndexOfMinimumTrace: [30×1 double]
          ObjectiveMinimumTrace: [30×1 double]
 EstimatedObjectiveMinimumTrace: [30×1 double]
```

Input Arguments

collapse all

`Tbl` — Sample data
table

Sample data used to train the model, specified as a table. Each row of `Tbl` corresponds to one observation, and each column corresponds to one predictor variable. Categorical predictor variables are not supported. Optionally, `Tbl` can contain one additional column for the response variable, which can be categorical. Multicolumn variables and cell arrays other than cell arrays of character vectors are not allowed.

- If `Tbl` contains the response variable, and you want to use all remaining variables in `Tbl` as predictors, then specify the response variable by using `ResponseVarName`.
- If `Tbl` contains the response variable, and you want to use only a subset of the remaining variables in `Tbl` as predictors, then specify a formula by using `formula`.
- If `Tbl` does not contain the response variable, then specify a response variable by using `Y`. The length of the response variable and the number of rows in `Tbl` must be equal.

`ResponseVarName` — Response variable name
name of variable in `Tbl`

Response variable name, specified as the name of a variable in `Tbl`.

You must specify `ResponseVarName` as a character vector or string scalar. For example, if the response variable `Y` is stored as `Tbl.Y`, then specify it as `"Y"`. Otherwise, the software treats all columns of `Tbl`, including `Y`, as predictors when training the model.

The response variable must be a categorical, character, or string array; a logical or numeric vector; or a cell array of character vectors. If `Y` is a character array, then each element of the response variable must correspond to one row of the array.

A good practice is to specify the order of the classes by using the `ClassNames` name-value argument.

Data Types: `char` | `string`

`formula` — Explanatory model of response variable and subset of predictor variables
character vector | string scalar

Explanatory model of the response variable and a subset of the predictor variables, specified as a character vector or string scalar in the form `"Y~x1+x2+x3"`. In this form, `Y` represents the response variable, and `x1`, `x2`, and `x3` represent the predictor variables.

To specify a subset of variables in `Tbl` as predictors for training the model, use a formula. If you specify a formula, then the software does not use any variables in `Tbl` that do not appear in `formula`.

The variable names in the formula must be both variable names in `Tbl` (`Tbl.Properties.VariableNames`) and valid MATLAB® identifiers. You can verify the variable names in `Tbl` by using the `isvarname` function. If the variable names are not valid, then you can convert them by using the `matlab.lang.makeValidName` function.

Data Types: `char` | `string`

`Y` — Class labels
categorical array | character array | string array | logical vector | numeric vector | cell array of character vectors

Class labels, specified as a categorical, character, or string array, a logical or numeric vector, or a cell array of character vectors. Each row of `Y` represents the classification of the corresponding row of `X`.

The software considers `NaN`, `''` (empty character vector), `""` (empty string), `<missing>`, and `<undefined>` values in `Y` to be missing values. Consequently, the software does not train using observations with a missing response.

Data Types: `categorical` | `char` | `string` | `logical` | `single` | `double` | `cell`

`X` — Predictor data
numeric matrix

Predictor values, specified as a numeric matrix. Each column of `X` represents one variable, and each row represents one observation. Categorical predictor variables are not supported.

`fitcdiscr` considers `NaN` values in `X` as missing values. `fitcdiscr` does not use observations with missing values for `X` in the fit.

Data Types: `single` | `double`

Name-Value Arguments

expand all

Specify optional pairs of arguments as `Name1=Value1,...,NameN=ValueN`, where `Name` is the argument name and `Value` is the corresponding value. Name-value arguments must appear after other arguments, but the order of the pairs does not matter.

Before R2021a, use commas to separate each name and value, and enclose `Name` *in quotes.*

Example: `'DiscrimType','quadratic','SaveMemory','on'` specifies a quadratic discriminant classifier and does not store the covariance matrix in the output object.

Note

You cannot use any cross-validation name-value argument together with the `OptimizeHyperparameters` name-value argument. You can modify the cross-validation for `OptimizeHyperparameters` only by using the `HyperparameterOptimizationOptions` name-value argument.

Model Parameters

collapse all

`ClassNames` — Names of classes to use for training

categorical array | character array | string array | logical vector | numeric vector | cell array of character vectors

Names of classes to use for training, specified as a categorical, character, or string array; a logical or numeric vector; or a cell array of character vectors. `ClassNames` must have the same data type as the response variable in `Tbl` or `Y`.

If `ClassNames` is a character array, then each element must correspond to one row of the array.

Use `ClassNames` to:

- Specify the order of the classes during training.
- Specify the order of any input or output argument dimension that corresponds to the class order. For example, use `ClassNames` to specify the order of the dimensions of `Cost` or the column order of classification scores returned by `predict`.
- Select a subset of classes for training. For example, suppose that the set of all distinct class names in `Y` is `["a","b","c"]`. To train the model using observations from classes `"a"` and `"c"` only, specify `ClassNames=["a","c"]`.

The default value for `ClassNames` is the set of all distinct class names in the response variable in `Tbl` or `Y`.

Example: `ClassNames=["b","g"]`

Data Types: `categorical` | `char` | `string` | `logical` | `single` | `double` | `cell`

`Cost` — Cost of misclassification

square matrix | structure

Cost of misclassification of a point, specified as one of the following:

- Square matrix, where `Cost(i,j)` is the cost of classifying a point into class `j` if its true class is `i` (that is, the rows correspond to the true class and the columns correspond to the predicted class). To specify the class order for the corresponding rows and columns of `Cost`, additionally specify the `ClassNames` name-value pair argument.
- Structure `S` having two fields: `S.ClassNames` containing the group names as a variable of the same type as `Y`, and `S.ClassificationCosts` containing the cost matrix.

The default is `Cost(i,j)=1` if `i~=j`, and `Cost(i,j)=0` if `i=j`.

Data Types: `single` | `double` | `struct`

`Delta` — Linear coefficient threshold

`0` (default) | nonnegative scalar value

Linear coefficient threshold, specified as the comma-separated pair consisting of `'Delta'` and a nonnegative scalar value. If a coefficient of `Mdl` has magnitude smaller than `Delta`, `Mdl` sets this coefficient to `0`, and you can eliminate the corresponding predictor from the model. Set `Delta` to a higher value to eliminate more predictors.

`Delta` must be `0` for quadratic discriminant models.

Data Types: `single` | `double`

`DiscrimType` — Discriminant type
`'linear'` (default) | `'quadratic'` | `'diaglinear'` | `'diagquadratic'` | `'pseudolinear'` | `'pseudoquadratic'`

Discriminant type, specified as the comma-separated pair consisting of `'DiscrimType'` and a character vector or string scalar in this table.

Value	Description	Predictor Covariance Treatment
`'linear'`	Regularized linear discriminant analysis (LDA)	• All classes have the same covariance matrix. • $\widehat{\Sigma}_\gamma = (1-\gamma)\widehat{\Sigma} + \gamma \mathrm{diag}(\widehat{\Sigma}).$ $\widehat{\Sigma}$ is the empirical, pooled covariance matrix and γ is the amount of regularization.
`'diaglinear'`	LDA	All classes have the same, diagonal covariance matrix.
`'pseudolinear'`	LDA	All classes have the same covariance matrix. The software inverts the covariance matrix using the pseudo inverse.
`'quadratic'`	Quadratic discriminant analysis (QDA)	The covariance matrices can vary among classes.
`'diagquadratic'`	QDA	The covariance matrices are diagonal and can vary among classes.
`'pseudoquadratic'`	QDA	The covariance matrices can vary among classes. The software inverts the covariance matrix using the pseudo inverse.

> **Note**
>
> To use regularization, you must specify `'linear'`. To specify the amount of regularization, use the `Gamma` name-value pair argument.

Example: `'DiscrimType','quadratic'`

`FillCoeffs` — `Coeffs` property flag
`'on'` | `'off'`

Coeffs property flag, specified as the comma-separated pair consisting of 'FillCoeffs' and 'on' or 'off'. Setting the flag to 'on' populates the Coeffs property in the classifier object. This can be computationally intensive, especially when cross-validating. The default is 'on', unless you specify a cross-validation name-value pair, in which case the flag is set to 'off' by default.

Example: 'FillCoeffs','off'

Gamma — Amount of regularization
scalar value in the interval [0,1]

Amount of regularization to apply when estimating the covariance matrix of the predictors, specified as the comma-separated pair consisting of 'Gamma' and a scalar value in the interval [0,1]. Gamma provides finer control over the covariance matrix structure than DiscrimType.

- If you specify 0, then the software does not use regularization to adjust the covariance matrix. That is, the software estimates and uses the unrestricted, empirical covariance matrix.
  - For linear discriminant analysis, if the empirical covariance matrix is singular, then the software automatically applies the minimal regularization required to invert the covariance matrix. You can display the chosen regularization amount by entering Mdl.Gamma at the command line.
  - For quadratic discriminant analysis, if at least one class has an empirical covariance matrix that is singular, then the software throws an error.
- If you specify a value in the interval (0,1), then you must implement linear discriminant analysis, otherwise the software throws an error. Consequently, the software sets DiscrimType to 'linear'.
- If you specify 1, then the software uses maximum regularization for covariance matrix estimation. That is, the software restricts the covariance matrix to be diagonal. Alternatively, you can set DiscrimType to 'diagLinear' or 'diagQuadratic' for diagonal covariance matrices.

Example: 'Gamma',1

Data Types: single | double

PredictorNames — Predictor variable names
string array of unique names | cell array of unique character vectors

Predictor variable names, specified as a string array of unique names or cell array of unique character vectors. The functionality of PredictorNames depends on the way you supply the training data.

- If you supply X and Y, then you can use PredictorNames to assign names to the predictor variables in X.
  - The order of the names in PredictorNames must correspond to the column order of X. That is, PredictorNames{1} is the name of X(:,1), PredictorNames{2} is the name of X(:,2), and so on. Also, size(X,2) and numel(PredictorNames) must be equal.
  - By default, PredictorNames is {'x1','x2',...}.
- If you supply Tbl, then you can use PredictorNames to choose which predictor variables to use in training. That is, fitcdiscr uses only the predictor variables in PredictorNames and the response variable during training.
  - PredictorNames must be a subset of Tbl.Properties.VariableNames and cannot include the name of the response variable.
  - By default, PredictorNames contains the names of all predictor variables.
  - A good practice is to specify the predictors for training using either PredictorNames or formula, but not both.

Example: "PredictorNames",["SepalLength","SepalWidth","PetalLength","PetalWidth"]
Data Types: string | cell

Prior — Prior probabilities
"empirical" (default) | "uniform" | vector of scalar values | structure

Prior probabilities for each class, specified as a value in this table.

Value	Description
"empirical"	The class prior probabilities are the class relative frequencies in Y.
"uniform"	All class prior probabilities are equal to $1/K$, where K is the number of classes.
numeric vector	Each element is a class prior probability. Order the elements according to Mdl.ClassNames or specify the order using the ClassNames name-value pair argument. The software normalizes the elements such that they sum to 1.
structure	A structure S with two fields: • S.ClassNames contains the class names as a variable of the same type as Y. • S.ClassProbs contains a vector of corresponding prior probabilities. The software normalizes the elements such that they sum to 1.

If you set values for both Weights and Prior, the weights are renormalized to add up to the value of the prior probability in the respective class.

Example: Prior="uniform"

Data Types: char | string | single | double | struct

ResponseName — Response variable name
"Y" (default) | character vector | string scalar

Response variable name, specified as a character vector or string scalar.

- If you supply Y, then you can use ResponseName to specify a name for the response variable.
- If you supply ResponseVarName or formula, then you cannot use ResponseName.

Example: ResponseName="response"

Data Types: char | string

SaveMemory — Flag to save covariance matrix
'off' (default) | 'on'

Flag to save covariance matrix, specified as the comma-separated pair consisting of `'SaveMemory'` and either `'on'` or `'off'`. If you specify `'on'`, then `fitcdiscr` does not store the full covariance matrix, but instead stores enough information to compute the matrix. The `predict` method computes the full covariance matrix for prediction, and does not store the matrix. If you specify `'off'`, then `fitcdiscr` computes and stores the full covariance matrix in `Mdl`.

Specify `SaveMemory` as `'on'` when the input matrix contains thousands of predictors.

Example: `'SaveMemory','on'`

`ScoreTransform` — Score transformation
`"none"` (default) | `"doublelogit"` | `"invlogit"` | `"ismax"` | `"logit"` | function handle | ...

Score transformation, specified as a character vector, string scalar, or function handle.

This table summarizes the available character vectors and string scalars.

Value	Description
`"doublelogit"`	$1/(1 + e^{-2x})$
`"invlogit"`	$\log(x / (1 - x))$
`"ismax"`	Sets the score for the class with the largest score to 1, and sets the scores for all other classes to 0
`"logit"`	$1/(1 + e^{-x})$
`"none"` or `"identity"`	x (no transformation)
`"sign"`	−1 for $x < 0$ 0 for $x = 0$ 1 for $x > 0$
`"symmetric"`	$2x - 1$
`"symmetricismax"`	Sets the score for the class with the largest score to 1, and sets the scores for all other classes to −1
`"symmetriclogit"`	$2/(1 + e^{-x}) - 1$

For a MATLAB function or a function you define, use its function handle for the score transform. The function handle must accept a matrix (the original scores) and return a matrix of the same size (the transformed scores).

Example: `ScoreTransform="logit"`

Data Types: `char` | `string` | `function_handle`

`Weights` — Observation weights
numeric vector of positive values | name of variable in `Tbl`

Observation weights, specified as a numeric vector of positive values or name of a variable in `Tbl`. The software weighs the observations in each row of `X` or `Tbl` with the corresponding value in `Weights`. The size of `Weights` must equal the number of rows of `X` or `Tbl`.

If you specify the input data as a table `Tbl`, then `Weights` can be the name of a variable in `Tbl` that contains a numeric vector. In this case, you must specify `Weights` as a character vector or string scalar. For example, if the weights vector `W` is stored as `Tbl.W`, then specify it as `"W"`. Otherwise, the software treats all columns of `Tbl`, including `W`, as predictors or the response when training the model.

By default, `Weights` is `ones(n,1)`, where *n* is the number of observations in `X` or `Tbl`.

The software normalizes `Weights` to sum up to the value of the prior probability in the respective class. `Inf` weights are not supported.
Data Types: `double` | `single` | `char` | `string`

Cross-Validation Options

collapse all

`CrossVal` — Cross-validation flag
`'off'` (default) | `'on'`

Cross-validation flag, specified as the comma-separated pair consisting of `'Crossval'` and `'on'` or `'off'`.

If you specify `'on'`, then the software implements 10-fold cross-validation.

To override this cross-validation setting, use one of these name-value pair arguments: `CVPartition`, `Holdout`, `KFold`, or `Leaveout`. To create a cross-validated model, you can use one cross-validation name-value pair argument at a time only.

Alternatively, cross-validate later by passing `Mdl` to `crossval`.

Example: `'CrossVal','on'`

`CVPartition` — Cross-validation partition
`[]` (default) | `cvpartition` object

Cross-validation partition, specified as a `cvpartition` object that specifies the type of cross-validation and the indexing for the training and validation sets.

To create a cross-validated model, you can specify only one of these four name-value arguments: `CVPartition`, `Holdout`, `KFold`, or `Leaveout`.

Example: Suppose you create a random partition for 5-fold cross-validation on 500 observations by using `cvp = cvpartition(500,KFold=5)`. Then, you can specify the cross-validation partition by setting `CVPartition=cvp`.

`Holdout` — Fraction of data for holdout validation
scalar value in the range (0,1)

Fraction of the data used for holdout validation, specified as a scalar value in the range (0,1). If you specify `Holdout=p`, then the software completes these steps:

1. Randomly select and reserve `p*100%` of the data as validation data, and train the model using the rest of the data.
2. Store the compact trained model in the `Trained` property of the cross-validated model.

To create a cross-validated model, you can specify only one of these four name-value arguments: `CVPartition`, `Holdout`, `KFold`, or `Leaveout`.

Example: `Holdout=0.1`

Data Types: `double` | `single`

`KFold` — **Number of folds**
`10` (default) | positive integer value greater than 1

Number of folds to use in the cross-validated model, specified as a positive integer value greater than 1. If you specify `KFold=k`, then the software completes these steps:

1. Randomly partition the data into `k` sets.
2. For each set, reserve the set as validation data, and train the model using the other `k` – 1 sets.
3. Store the `k` compact trained models in a `k`-by-1 cell vector in the `Trained` property of the cross-validated model.

To create a cross-validated model, you can specify only one of these four name-value arguments: `CVPartition`, `Holdout`, `KFold`, or `Leaveout`.

Example: `KFold=5`

Data Types: `single` | `double`

`Leaveout` — **Leave-one-out cross-validation flag**
`"off"` (default) | `"on"`

Leave-one-out cross-validation flag, specified as `"on"` or `"off"`. If you specify `Leaveout="on"`, then for each of the n observations (where n is the number of observations, excluding missing observations, specified in the `NumObservations` property of the model), the software completes these steps:

1. Reserve the one observation as validation data, and train the model using the other n – 1 observations.
2. Store the n compact trained models in an n-by-1 cell vector in the `Trained` property of the cross-validated model.

To create a cross-validated model, you can specify only one of these four name-value arguments: `CVPartition`, `Holdout`, `KFold`, or `Leaveout`.

Example: `Leaveout="on"`

Data Types: `char` | `string`

Hyperparameter Optimization Options

expand all

`OptimizeHyperparameters` — **Parameters to optimize**
`'none'` (default) | `'auto'` | `'all'` | string array or cell array of eligible parameter names | vector of `optimizableVariable` objects

Parameters to optimize, specified as the comma-separated pair consisting of `'OptimizeHyperparameters'` and one of the following:

- `'none'` — Do not optimize.
- `'auto'` — Use `{'Delta','Gamma'}`.
- `'all'` — Optimize all eligible parameters.
- String array or cell array of eligible parameter names.
- Vector of `optimizableVariable` objects, typically the output of `hyperparameters`.

The optimization attempts to minimize the cross-validation loss (error) for `fitcdiscr` by varying the parameters. To control the cross-validation type and other aspects of the optimization, use the `HyperparameterOptimizationOptions` name-value argument. When you use `HyperparameterOptimizationOptions`, you can use the (compact) model size instead of the cross-validation loss as the optimization objective by setting the `ConstraintType` and `ConstraintBounds` options.

Note

The values of `OptimizeHyperparameters` override any values you specify using other name-value arguments. For example, setting `OptimizeHyperparameters` to `"auto"` causes `fitcdiscr` to optimize hyperparameters corresponding to the `"auto"` option and to ignore any specified values for the hyperparameters.

The eligible parameters for `fitcdiscr` are:

- `Delta` — `fitcdiscr` searches among positive values, by default log-scaled in the range `[1e-6,1e3]`.
- `DiscrimType` — `fitcdiscr` searches among `'linear'`, `'quadratic'`, `'diagLinear'`, `'diagQuadratic'`, `'pseudoLinear'`, and `'pseudoQuadratic'`.
- `Gamma` — `fitcdiscr` searches among real values in the range `[0,1]`.

Set nondefault parameters by passing a vector of `optimizableVariable` objects that have nondefault values. For example,

```
load fisheriris
params = hyperparameters('fitcdiscr',meas,species);
params(1).Range = [1e-4,1e6];
```

Pass `params` as the value of `OptimizeHyperparameters`.

By default, the iterative display appears at the command line, and plots appear according to the number of hyperparameters in the optimization. For the optimization and plots, the objective function is the misclassification rate. To control the iterative display, set the `Verbose` option of the `HyperparameterOptimizationOptions` name-value argument. To control the plots, set the `ShowPlots` field of the `HyperparameterOptimizationOptions` name-value argument.

For an example, see Optimize Discriminant Analysis Model.

Example: `'auto'`

`HyperparameterOptimizationOptions` — Options for optimization
`HyperparameterOptimizationOptions` object | structure

Output Arguments

collapse all

`Mdl` — Trained discriminant analysis classification model
`ClassificationDiscriminant` model object | `ClassificationPartitionedModel` cross-validated model object

Trained discriminant analysis classification model, returned as a `ClassificationDiscriminant` model object or a `ClassificationPartitionedModel` cross-validated model object.

If you set any of the name-value pair arguments `KFold`, `Holdout`, `CrossVal`, or `CVPartition`, then `Mdl` is a `ClassificationPartitionedModel` cross-validated model object. Otherwise, `Mdl` is a `ClassificationDiscriminant` model object.

To reference properties of `Mdl`, use dot notation. For example, to display the estimated component means at the Command Window, enter `Mdl.Mu`.

If you specify `OptimizeHyperparameters` and set the `ConstraintType` and `ConstraintBounds` options of `HyperparameterOptimizationOptions`, then `Mdl` is an N-by-1 cell array of model objects, where N is equal to the number of rows in `ConstraintBounds`. If none of the optimization problems yields a feasible model, then each cell array value is `[]`.

`AggregateOptimizationResults` — Aggregate optimization results
`AggregateBayesianOptimization` object

Aggregate optimization results for multiple optimization problems, returned as an `AggregateBayesianOptimization` object. To return `AggregateOptimizationResults`, you must specify `OptimizeHyperparameters` and `HyperparameterOptimizationOptions`. You must also specify the `ConstraintType` and `ConstraintBounds` options of `HyperparameterOptimizationOptions`. For an example that shows how to produce this output, see Hyperparameter Optimization with Multiple Constraint Bounds.

More About

collapse all

Discriminant Classification

The model for discriminant analysis is:

- Each class (`Y`) generates data (`X`) using a multivariate normal distribution. That is, the model assumes `X` has a Gaussian mixture distribution (`gmdistribution`).
    - For linear discriminant analysis, the model has the same covariance matrix for each class, only the means vary.
    - For quadratic discriminant analysis, both means and covariances of each class vary.

`predict` classifies so as to minimize the expected classification cost:

$$\hat{y} = \underset{y=1,\dots,K}{\operatorname{argmin}} \sum_{k=1}^{K} \hat{P}(k|x)C(y|k),$$

where

- $\hat{y}$ is the predicted classification.
- K is the number of classes.
- $\hat{P}(k|x)$ is the posterior probability of class k for observation x.
- $C(y|k)$ is the cost of classifying an observation as y when its true class is k.

For details, see Prediction Using Discriminant Analysis Models.

Tips

After training a model, you can generate C/C++ code that predicts labels for new data. Generating C/C++ code requires MATLAB Coder™. For details, see Introduction to Code Generation.

Algorithms

- If you specify the `Cost`, `Prior`, and `Weights` name-value arguments, the output model object stores the specified values in the `Cost`, `Prior`, and `W` properties, respectively. The `Cost` property stores the user-specified cost matrix as is. The `Prior` and `W` properties store the prior probabilities and observation weights, respectively, after normalization. For details, see Misclassification Cost Matrix, Prior Probabilities, and Observation Weights.

- The software uses the `Cost` property for prediction, but not training. Therefore, `Cost` is not read-only; you can change the property value by using dot notation after creating the trained model.

Alternative Functionality

Functions

The `classify` function also performs discriminant analysis. `classify` is usually more awkward to use.

- `classify` requires you to fit the classifier every time you make a new prediction.
- `classify` does not perform cross-validation or hyperparameter optimization.
- `classify` requires you to fit the classifier when changing prior probabilities.

Extended Capabilities

expand all

Tall Arrays
Calculate with arrays that have more rows than fit in memory.

Automatic Parallel Support
Accelerate code by automatically running computation in parallel using Parallel Computing Toolbox™.

Version History

expand all

Introduced in R2014a

R2025a: Compute serially when parallel hyperparameter optimization is not available⚠

See Also

`ClassificationDiscriminant` | `ClassificationPartitionedModel` | `predict` | `crossval` | `classify`

Topics

Discriminant Analysis Classification

Improving Discriminant Analysis Models

Regularize Discriminant Analysis Classifier