Label Predictions

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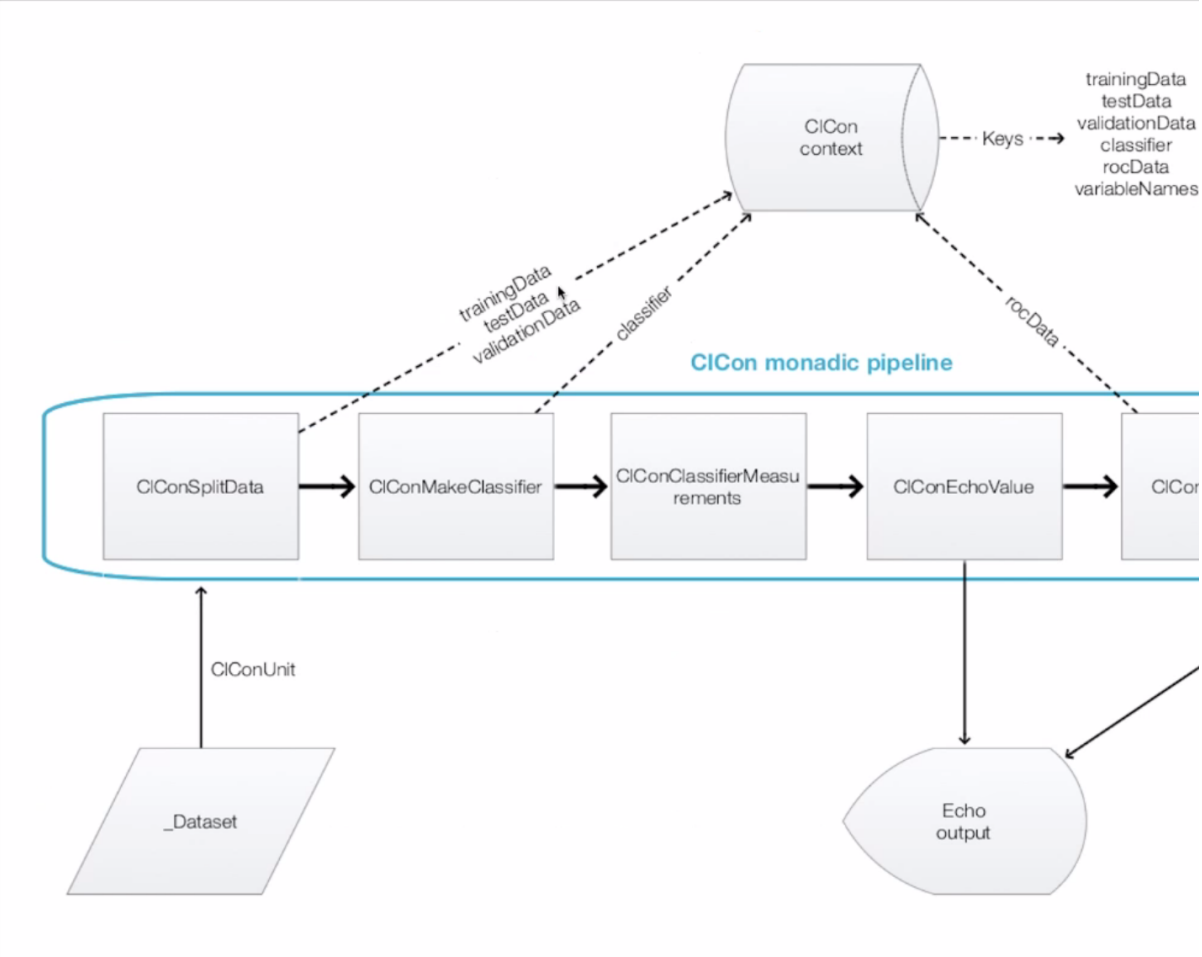
I specifically used a package called MonadicContextualClassification, that provides functions for classification with classifiers with contexts and the documentation can be found here. The package is also discussed in this community forum. The figure below outlines the classification process in the pipeline.



Mathematica is a computation program well known for technical computing such as machine learning and it uses Wolfram language, that is a multi-paradigm, functional language. In the rest of the notebook we start with data load and wrangling (Chapter 1 and Chapter 2), continue with

several dimension reduction attempts on the training data and training the classifiers accordingly (Chapter 3). We also present the prediction results in Section 3.3.4. Lastly, we do comparisons on classifiers and sum up the learnings (Chapter 4).

1. Data load

```
Import[
  "https://raw.githubusercontent.com/antononcube/MathematicaForPrediction/
    master/MonadicProgramming/MonadicContextualClassification.m"];
Import[
  "https://raw.githubusercontent.com/antononcube/MathematicaForPrediction/
    master/MathematicaForPredictionUtilities.m"];
Import[
  "https://raw.githubusercontent.com/antononcube/MathematicaForPrediction/
    master/MosaicPlot.m"];

Training = Import["/Users/yaman/Desktop/homework_48/train_data.csv"];
Tlabels = Import["/Users/yaman/Desktop/homework_48/train_labels.csv"];
testingCSVData = Import["/Users/yaman/Desktop/homework_48/test_data.csv"];

Dimensions[Training]
Dimensions[Tlabels]
Dimensions[testingCSVData]
```

```
{3750, 10 000}

{3750, 1}

{1250, 10 000}
```

2. Data wrangling

```
Tally[Tlabels]
mlData = MapThread[Rule, {Training, Tlabels[[All, 1]]}];
Short /@ mlData[[1 ;; 6]]
```

```
{{{1}, 3378}, {{-1}, 372}}

{{620.643, -225.484, -131 214., 83 536.7, <<9993>>, 133.456, -344.193, 626.785} → 1,
 {789.336, 158.857, -8422.37, 54 747.6, <<9992>>, 32.379,
   -418.297, -292.736, -390.922} → 1, {-323.514, -520.415,
   -43 709.2, 150 098., <<9993>>, -684.42, -1878.7, -31.079} → 1,
 {280.384, 4.955, -13 609.3, -141 966., <<9993>>, -496.787, -205.806, -240.249} →
  1, {15.483, -98.902, 37 406., 138 522., <<9993>>, -650.591, -45.142, 678.672} → 1,
 {575.561, -345.999, 28 541.3, 20 939.8, <<9993>>,
   -232.023, -436.482, -158.154} → 1}
```

Now we merged labels with the training data and put it in the right form. One observation is that

the labels are mostly 1's. Dimension reduction could be wise to apply.

3. Attempts with dimension reduction

3.1 First try with 12 dimensions

In this section, let's first try apply low-rank SVD to the training data in order to reduce the dimension to 12 basis vectors and train a classifier.

```
RecordsSummary[Mean[mlData[[All, 1]]]]
```

```
1 column 1
Min      -752.913
1st Qu   9.07144
Median   14.4814
3rd Qu   20.1494
Mean     25.3132
Max      85695.5
```

Apply SVD on training data:

```
svdRes0 = SingularValueDecomposition[mlData[[All, 1]], 12];
```

```
Dimensions /@ svdRes0
```

```
{{3750, 12}, {12, 12}, {10000, 12}}
```

Transform the data:

```
mlData2 = MapThread[Rule, {svdRes0[[1]], Tlabels[[All, 1]]}];
RecordsSummary[mlData2, Thread → True]
Short /@ mlData2[[1 ;; 6]]
```

1 column 1		2 column 2	
Min	−0.0381579	Min	−0.0565906
1st Qu	−0.0210219	1st Qu	−0.0111527
Median	−0.00738576	Mean	−0.000159545
Mean	−0.00720428	Median	−0.000100279
3rd Qu	0.00662302	3rd Qu	0.0111871
Max	0.0242548	Max	0.0557858

3 column 3		4 column 4		5 column 5	
Min	−0.052951	Min	−0.0599539	Min	−0.061953
1st Qu	−0.0107632	1st Qu	−0.0110121	1st Qu	−0.010073
Median	−0.000132896	Mean	0.000205514	Median	0.000720162
Mean	−0.0000214609	Median	0.00029938	Mean	0.000934545
3rd Qu	0.0109954	3rd Qu	0.0110236	3rd Qu	0.0118416
Max	0.0575035	Max	0.0598682	Max	0.0710834

6 column 6		7 column 7		8 column 8	
Min	−0.0297199	Min	−0.0594535	Min	−0.0592629
1st Qu	0.00227527	1st Qu	−0.0111447	1st Qu	−0.0113856
Median	0.0107471	Mean	−0.000328781	Median	−0.000422077
Mean	0.0108286	Median	−0.000220589	Mean	−0.000300383
3rd Qu	0.0190886	3rd Qu	0.0107263	3rd Qu	0.0107644
Max	0.0555419	Max	0.052272	Max	0.0558449

9 column 9		10 column 10	
Min	−0.059068	Min	−0.055769
1st Qu	−0.0111331	1st Qu	−0.0108419
Mean	−0.0000339777	Median	−0.000127776
Median	0.0000995472	Mean	0.000178098
3rd Qu	0.0108988	3rd Qu	0.0115082
Max	0.0591568	Max	0.068682

11 column 11		12 column 12		1 column 1	
Min	−0.0544622	Min	−0.0543678	Min	−1
1st Qu	−0.0112319	1st Qu	−0.0116429	Mean	0.8016
Mean	−0.000364756	Mean	−0.000676484	1st Qu	1
Median	−0.000239868	Median	−0.000644835	3rd Qu	1
3rd Qu	0.0104151	3rd Qu	0.0107174	Max	1
Max	0.0664438	Max	0.0577258	Median	1

```
{{-0.0196666, 0.0181426, <<8>>, 0.00563199, -0.00951586} → 1,
 {0.0101886, 0.0118767, <<8>>, -0.0213271, -0.00476392} → 1,
 {-0.0000171904, 0.0312215, <<8>>, 0.0147743, 0.0444562} → 1,
 {-0.016201, -0.0264471, <<8>>, -0.0117296, -0.0140664} → 1,
 {-0.0245408, 0.0242427, <<8>>, 0.00435455, -0.0121917} → 1,
 {0.00508833, 0.00389178, <<8>>, 0.00909727, 0.0153733} → 1}
```

Just checking the matrices:

```
Dimensions[Transpose[svdRes0[[3]]]]
```

```
{12, 10 000}
```

```
(Transpose[svdRes0[[3]]].mlData[[All, 1]][[1]]).Inverse[svdRes0[[2]]]
```

```
{-0.0196666, 0.0181426, -0.000189024, 0.030512, -0.00589098, 0.00772635,
 0.00553564, -0.00243173, 0.00881216, -0.00323336, 0.00563199, -0.00951586}
```

```
(svdRes0[[2]].Transpose[svdRes0[[3]]]).mlData[[All, 1]][[1]]
```

$$\{-2.98112\times10^{12},\ 4.71313\times10^{11},\ -3.86983\times10^{9},\ 5.26083\times10^{11},\ -4.69739\times10^{9},\ 1.03906\times10^{8},\ 6.83239\times10^{7},\ -2.98397\times10^{7},\ 1.07748\times10^{8},\ -3.94221\times10^{7},\ 6.82547\times10^{7},\ -1.15225\times10^{8}\}$$

Now using the pipeline to get the classifier trained and see the performance:

```
res1 = ClConUnit[mlData2] ⟹
   ClConModifyContext[Join[#, <|
       "variableNames" → Map[ToString, Range[Length[mlData2[[1, 1]]] + 1]]|>] &] ⟹
   ClConSplitData[0.8] ⟹
   ClConAddToContext ⟹
   ClConSummarizeData[] ⟹
   ClConMakeClassifier["RandomForest"] ⟹
   ClConEchoFunctionContext[
    Magnify[ClassifierInformation[#["classifier"]], 0.6] &] ⟹
   ClConClassifierMeasurements[{"Accuracy", "Precision", "Recall"}] ⟹
   ClConEchoValue ⟹
   ClConROCPlot[] ⟹
   ClConAccuracyByVariableShuffling[] ⟹
   ClConEchoValue;
```

» summaries: {trainingData → {1 RowID: 1 13, 10 13, 100 13, 1000 13, 1001 13, 1002 13, (Other) 38 909; 2 Variable: 1 2999, 10 2999, 11 2999, 12 2999, 13 2999, 2 2999, (Other) 20 993; 3 Value: Min -1, 1st Qu -0.0103231, Median 0.00222063, 3rd Qu 0.0142016, Mean 0.0619617, Max 1},

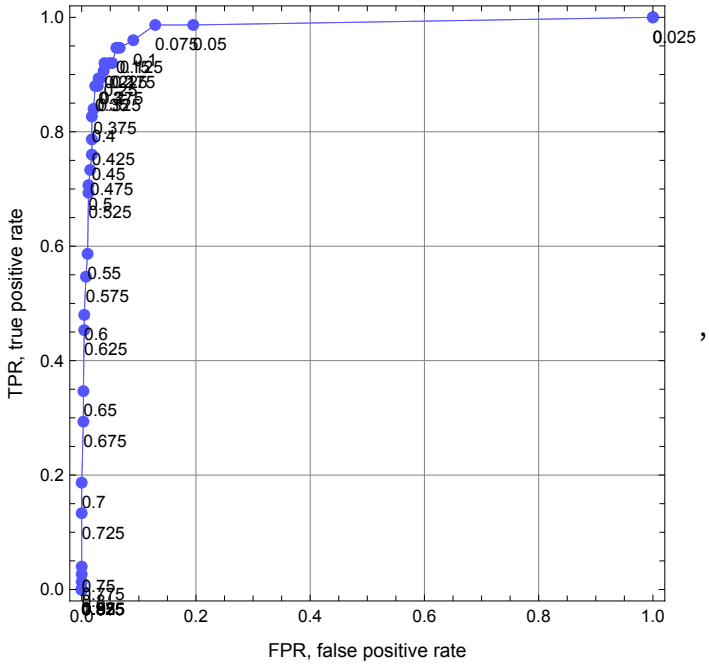
testData → {1 RowID: 1 13, 10 13, 100 13, 101 13, 102 13, 103 13, (Other) 9685; 2 Variable: 1 751, 10 751, 11 751, 12 751, 13 751, 2 751, (Other) 5257; 3 Value: Min -1, 1st Qu -0.0104268, Median 0.00193534, 3rd Qu 0.0140685, Mean 0.061637, Max 1}}

» Classifier information

Method	Random forest
Number of classes	2
Number of features	1
Number of training examples	2999
Number of trees	50

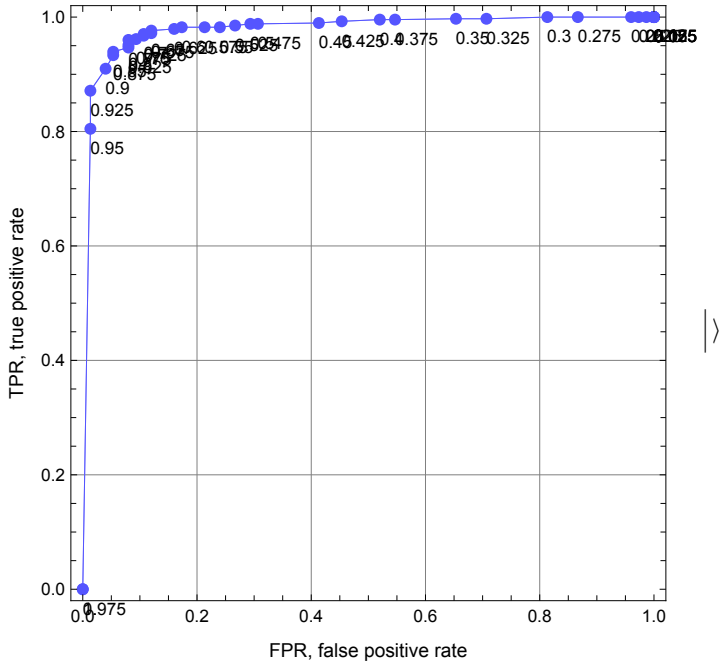
» value: ⟨|Accuracy → 0.960053, Precision → ⟨|-1 → 0.868852, 1 → 0.968116|⟩, Recall → ⟨|-1 → 0.706667, 1 → 0.988166|⟩|⟩

» ROC plot(s): ⟨| -1 →



,

1 →



|⟩

» value: ‹| None → 0.960053, 1 → 0.829561, 2 → 0.960053,
3 → 0.958722, 4 → 0.956059, 5 → 0.950732, 6 → 0.95739, 7 → 0.956059,
8 → 0.962716, 9 → 0.961385, 10 → 0.958722, 11 → 0.958722, 12 → 0.958722 |›

We extract the classifier:

```
cf1 = res1⟹ClConTakeClassifier
```

ClassifierFunction[ Input type: NumericalVector (length: 12)
Classes: −1, 1
Method: RandomForest
Number of training examples: 2999]

3.2 Separation before transformation (study phase)

In this section let's split the data before transformation and try more with SVD. We will utilize the SVD in two study ways: in the first study we extract the most decisive vectors and filter the training set based on them (Section 3.2.1). in the second study we go with predefined dimension space, and use validation data for classification pipeline (Section 3.2.2).

3.2.1 Most significant vectors

```
mlData = MapThread[Rule, {Training, Tlabels[[All, 1]]}];
```

Separating the data at 0.75:

```
SeedRandom[123]
{trainingData, testData} =
  TakeDrop[RandomSample[mlData], Floor[0.75 * Length[mlData]]];
```

```
meanRow = Mean[trainingData[[All, 1]]];
RecordsSummary[meanRow]
```

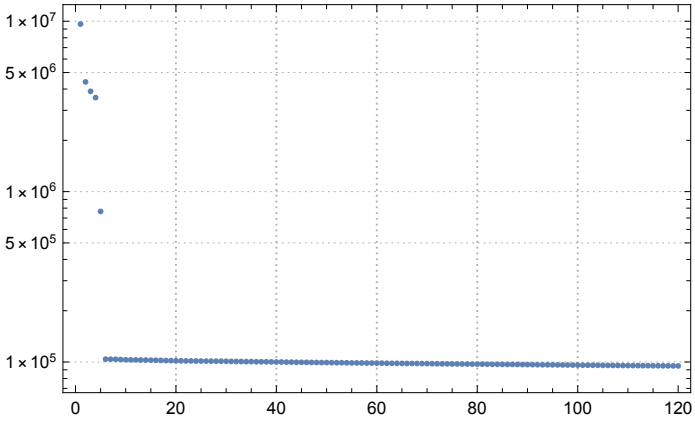
```
1 column 1
Min      -1131.99
1st Qu   8.22631
Median   14.6834
3rd Qu   20.9983
Mean     25.0205
Max      83377.9
```

apply SVD:

```
svdRes = SingularValueDecomposition[Map[# - meanRow &, trainingData[[All, 1]]], 120];
```

Let's see the most significant ones on a plot:

```
ListLogPlot[Diagonal[svdRes[[2]]], PlotRange → All, PlotTheme → "Detailed"]
```

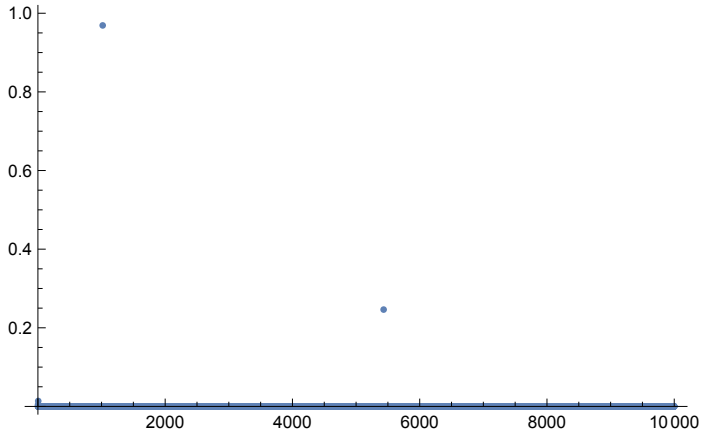


```
RecordsSummary[svdRes[[3, All, 1]]]
```

1 column 1	
Min	-0.000354587
1st Qu	-0.0000316648
Median	4.11535×10^{-7}
3rd Qu	0.0000316302
Mean	0.000123808
Max	0.969048

We can get the positions of most representative vectors:

```
ListPlot[Abs[svdRes[[3, All, 1]]], PlotRange → All, PlotStyle → {PointSize[0.01]}]
```




```
pos = Flatten@Position[Abs[svdRes[[3, All, 1]]], x_ /; x > 0.1]
```

```
{1018, 5433}
```

Transform the data with those vectors:

```
trainingData2 = Thread[(trainingData[[All, 1]][[All, pos]]) → trainingData[[All, 2]]];
testData2 = Thread[(testData[[All, 1]][[All, pos]]) → testData[[All, 2]]];

res =
  ClConUnit[<|"trainingData" → trainingData2, "testData" → testData2|>] ⟹
   ClConAddToContext ⟹
   ClConAssignVariableNames[] ⟹
   ClConEchoVariableNames[] ⟹
   ClConMakeClassifier["RandomForest"] ⟹
   ClConEchoFunctionContext[
    Magnify[ClassifierInformation[#["classifier"]], 0.8] &] ⟹
   ClConClassifierMeasurements[] ⟹ ClConEchoValue ⟹
   ClConROCPlot[] ⟹
   ClConClassifierMeasurementsByThreshold[
    {"Accuracy", "Precision", "Recall"}, -1 → 0.275] ⟹ ClConEchoValue ⟹
   ClConROCListLinePlot[{"TPR", "FPR", "PPV", "ACC"}] ⟹
   ClConAccuracyByVariableShuffling[] ⟹
   ClConEchoValue;
```

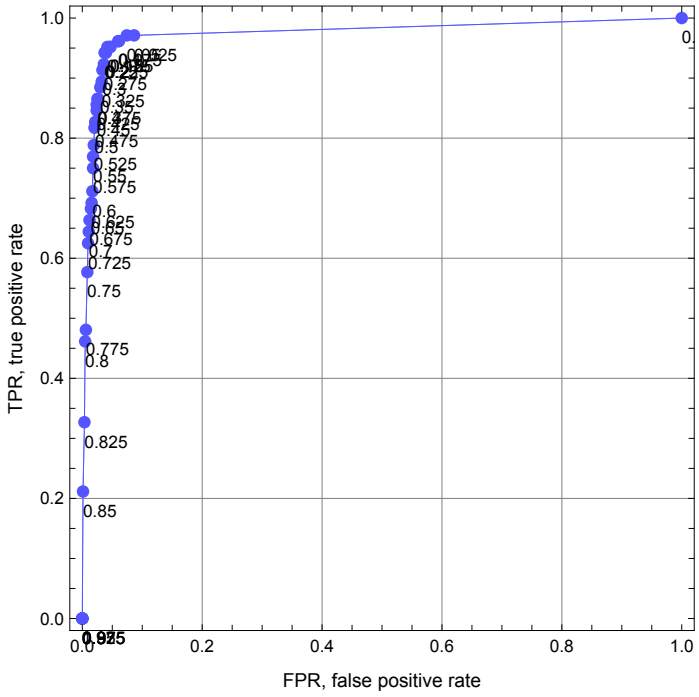
» variable names: {1, 2, 3}

»

Classifier information	
Method	Random forest
Number of classes	2
Number of features	1
Number of training examples	2812
Number of trees	50

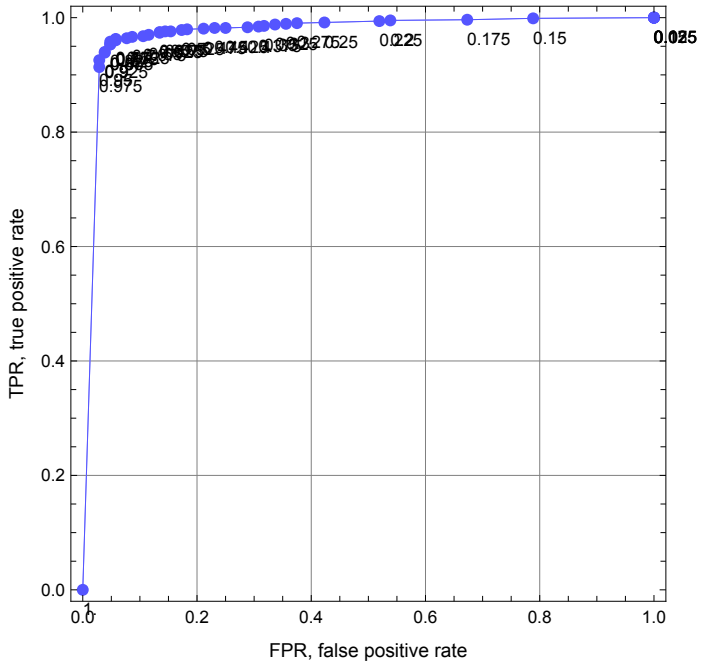
» value: ⟨|Accuracy → 0.96162, Precision → ⟨|-1 → 0.833333, 1 → 0.977273|⟩, Recall → ⟨|-1 → 0.817308, 1 → 0.979616|⟩|⟩

» ROC plot(s): ⟨|-1 →



,

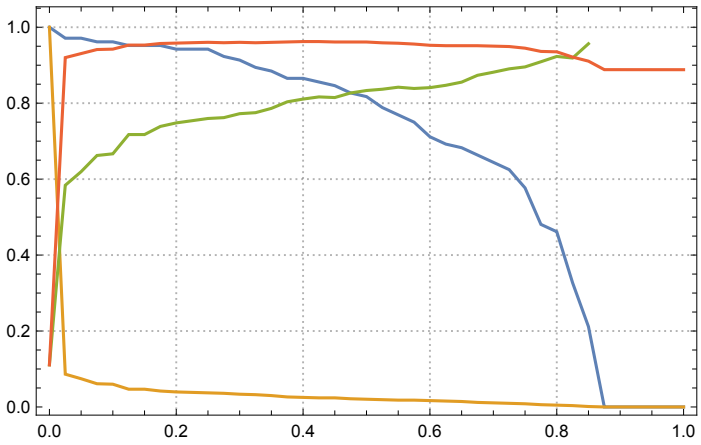
1 →



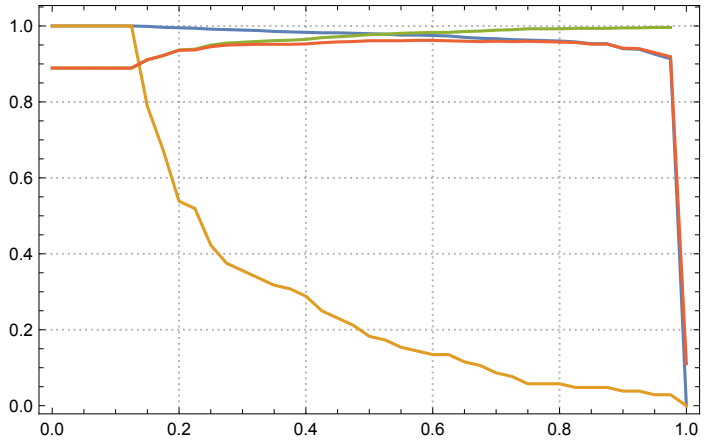
|⟩

» value: ⟨|Accuracy → 0.959488, Precision → ⟨|-1 → 0.761905, 1 → 0.990148|⟩, Recall → ⟨|-1 → 0.923077, 1 → 0.964029|⟩|⟩

» ROC line plot(s): ⟨| −1 →



,



1 → |⟩

» value: ‹| None → 0.96162, 1 → 0.50533, 2 → 0.491471 |›

Extract classify function for later use:

```
cf2 = First@Values[res⟹ClConTakeClassifier]
```

ClassifierFunction[Input type: NumericalVector (length: 2)
Classes: −1, 1
Method: RandomForest
Number of training examples: 2812]

3.2.2 SVD with 7 dimensions

Let's also try SVD with 7 dimensions:

```
svdRes2 = SingularValueDecomposition[trainingData[[All, 1]], 7];
```

$$U_{training} \cdot S_{training} \cdot V_{training}^{T} = M_{training} \tag{1}$$

Transform the training data accordingly:

```
trainingData3 = Thread[svdRes2[[1]].svdRes2[[2]] → trainingData[[All, 2]]];
RecordsSummary[trainingData3, Thread → True]
```

1 column 1		2 column 2		3 column 3		4 column 4	
Min	−298 465.	Min	−288 246.	Min	−238 981.	Min	−242 301.
1st Qu	−84 088.2	1st Qu	−55 974.5	1st Qu	−48 335.8	1st Qu	−44 312.6
Median	80 025.2	Mean	−813.065	Median	−536.749	Mean	1313.4
Mean	86 291.3	Median	138.512	Mean	165.231	Median	1879.07
3rd Qu	258 231.	3rd Qu	58 351.3	3rd Qu	49 267.7	3rd Qu	46 498.6
Max	469 033.	Max	275 836.	Max	266 371.	Max	247 579.

5 column 5		6 column 6		7 column 7		1 column 1	
Min	−55 310.8	Min	−4251.33	Min	−7382.6	Min	−1
1st Qu	−9052.99	1st Qu	216.514	1st Qu	−1348.82	Mean	0.809388
Median	491.734	Median	1286.93	Mean	4.49685	1st Qu	1
Mean	817.687	Mean	1289.78	Median	28.7751	3rd Qu	1
3rd Qu	10 629.	3rd Qu	2350.72	3rd Qu	1312.73	Max	1
Max	63 476.4	Max	7472.42	Max	7103.8	Median	1

Checking the dimensions:

```
Dimensions[Transpose[svdRes2[[3]]]]
Dimensions[testData[[All, 1]]]
```

```
{7, 10 000}
```

```
{938, 10 000}
```

Apply the data transformation (dimension reduction by SVD) to the test data part. Note that the SVD matrices used in the transformation were obtained from the training data only.

```
testData3 = (testData[[All, 1]].svdRes2[[3]]).Inverse[svdRes2[[2]]];
testData3 = Thread[testData3 → testData[[All, 2]]];
RecordsSummary[testData3, Thread → True]
```

1 column 1		2 column 2	
Min	−0.0240018	Min	−0.0541148
1st Qu	−0.00703041	1st Qu	−0.0130513
Mean	0.00899725	Median	−0.000618487
Median	0.0103261	Mean	−0.000161726
3rd Qu	0.0245722	3rd Qu	0.0121271
Max	0.0423416	Max	0.0645679

3 column 3		4 column 4		5 column 5	
Min	−0.0639481	Min	−0.070204	Min	−0.0669441
1st Qu	−0.0125033	1st Qu	−0.0132991	1st Qu	−0.0108033
Median	−0.000142361	Median	−0.000739836	Mean	0.00138746
Mean	0.000252131	Mean	−0.000333725	Median	0.00160622
3rd Qu	0.0135501	3rd Qu	0.0126869	3rd Qu	0.0137321
Max	0.0634837	Max	0.0645032	Max	0.0747202

6 column 6		7 column 7		1 column 1	
Min	−0.0169354	Min	−0.0294562	Min	−1
1st Qu	0.00106553	1st Qu	−0.00526424	Mean	0.778252
Mean	0.0062887	Mean	0.0000276345	1st Qu	1
Median	0.00640261	Median	0.00016977	3rd Qu	1
3rd Qu	0.0117367	3rd Qu	0.00547389	Max	1
Max	0.0286047	Max	0.0271276	Median	1

Running the classification workflow:

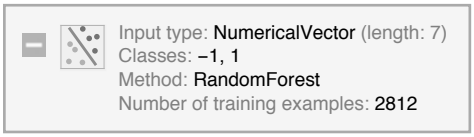
```
Dimensions[trainingData3]
Dimensions[testData3]
```

```
{2812}
```

```
{938}
```

This time let's only use the classify function:

```
cf3 = Classify[trainingData3, Method → "RandomForest", ValidationSet → testData3]
```

```
ClassifierFunction[ 
Input type: NumericalVector (length: 7)
Classes: −1, 1
Method: RandomForest
Number of training examples: 2812
]
```

3.3 Full cycle

Here finally we will use the unseen test set. But first, we treat mlData as training data and apply SVD with 8 dimensions (Section 3.3.1). Second, we build a classifier with both with a validation set and without (Section 3.3.2). Next we transform unseen test data in the reduced space (Section 3.3.3). Finally 3.3.4 will present the prediction results of selected classifiers.

3.3.1 Dimension reduction on the training data

```
mlData = MapThread[Rule, {Training, Tlabels[[All, 1]]}];
Short /@ mlData[[1 ;; 6]]
```

```
{{620.643, -225.484, -131214., 83536.7, <<9993>>, 133.456, -344.193, 626.785} → 1,
 {789.336, 158.857, -8422.37, <<9994>>, -418.297, -292.736, -390.922} → 1,
 {-323.514, -520.415, -43709.2, 150098., <<9993>>, -684.42, -1878.7, -31.079} →
  1, {280.384, 4.955, -13609.3, -141966.,
    <<9993>>, -496.787, -205.806, -240.249} → 1,
 {15.483, -98.902, 37406., 138522., <<9993>>, -650.591, -45.142, 678.672} → 1,
 {575.561, -345.999, 28541.3, 20939.8,
   <<9993>>, -232.023, -436.482, -158.154} → 1}
```

```
trainingDataFull = mlData;
```

```
AbsoluteTiming[
 svdRes3 = SingularValueDecomposition[trainingDataFull[[All, 1]], 8];
]
```

```
{29.1597, Null}
```

```
trainingData4 = Thread[svdRes3[[1]].svdRes3[[2]] → trainingDataFull[[All, 2]]];
```

```
RecordsSummary[trainingData4, Thread → True]
```

1 column 1		2 column 2		3 column 3	
Min	−469 797.	Min	−288 436.	Min	−239 586.
1st Qu	−258 819.	1st Qu	−56 844.	1st Qu	−48 699.9
Median	−90 932.8	Mean	−813.184	Median	−601.313
Mean	−88 698.5	Median	−511.109	Mean	−97.1035
3rd Qu	81 541.9	3rd Qu	57 019.6	3rd Qu	49 750.4
Max	298 622.	Max	284 334.	Max	260 185.

4 column 4		5 column 5		6 column 6	
Min	−248 948.	Min	−55 321.8	Min	−3446.52
1st Qu	−45 725.9	1st Qu	−8994.85	1st Qu	263.856
Mean	853.363	Median	643.08	Median	1246.31
Median	1243.13	Mean	834.516	Mean	1255.75
3rd Qu	45 773.6	3rd Qu	10 574.2	3rd Qu	2213.64
Max	248 593.	Max	63 475.	Max	6441.02

7 column 7		8 column 8		1 column 1	
Min	−6605.1	Min	−6564.82	Min	−1
1st Qu	−1238.15	1st Qu	−1261.23	Mean	0.8016
Mean	−36.5265	Median	−46.7553	1st Qu	1
Median	−24.5068	Mean	−33.2748	3rd Qu	1
3rd Qu	1191.65	3rd Qu	1192.43	Max	1
Max	5807.26	Max	6186.18	Median	1

3.3.2 Classifier building

We can create a classifier with a validation set (cf4), and also one without (cf5); and also one with using the pipeline (cf6).

```
{trainingData5, validationData5} =
  TakeDrop[trainingData4, Floor[0.9 * Length[trainingDataFull]]];
Length /@ {trainingData5, validationData5}
```

```
{3375, 375}
```

```
cf4 = Classify[trainingData5,
  Method → "RandomForest", ValidationSet → validationData5]
```

```
ClassifierFunction[ Input type: NumericalVector (length: 8)
                    Classes: −1, 1 ]
```

Let's train one without validation set:

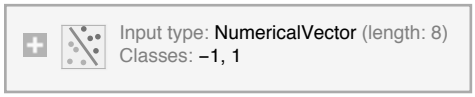
```
cf5 = Classify[trainingData4, Method → "RandomForest"]
```

```
ClassifierFunction[ Input type: NumericalVector (length: 8)
                    Classes: −1, 1 ]
```

Also one using the pipeline:

```
res5 =
  ClConUnit[<|"trainingData" → trainingData5,
     "testData" → {}, "validationData" -> validationData5|>] ⟹
   ClConAddToContext⟹
   ClConMakeClassifier["RandomForest"];
```

```
cf6 = res5⟹ClConTakeClassifier
```

ClassifierFunction[]

3.3.3 Transforming the unseen test data in reduced space

Finally we can transform the unseen test data, reduce it and call the classifier.

Checking the dimensions and the matrices first:

```
Dimensions[testingCSVData]
```

{1250, 10 000}

$$U_{training} . S_{training} . V_{training}^{T} = M_{traning} \tag{2}$$

```
Dimensions[svdRes3[[3]]]
```

{10 000, 8}

```
Diagonal[svdRes3[[2]]]
```

{1.23119 × 10^7, 5.09689 × 10^6, 4.52467 × 10^6,
 4.15233 × 10^6, 892 965., 115 967., 111 097., 110 774.}

```
Norm /@ Transpose[svdRes3[[3]]]
```

{1., 1., 1., 1., 1., 1., 1., 1.}

```
t = SparseArray[Transpose[svdRes3[[3]]].SparseArray[svdRes3[[3]]];
MatrixForm[Chop[t]]
```

$$\begin{pmatrix} 1. & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1. & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1. & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1. & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1. & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1. & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1. & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1. \end{pmatrix}$$

```
Dimensions[testingCSVData]
```

{1250, 10 000}

```
testData5 = testingCSVData.svdRes3[[3]];
Dimensions[testData5]
```

{1250, 8}

```
RecordsSummary[testData5]
```

1 column 1		2 column 2		3 column 3		4 column 4	
Min	−456 583.	Min	−331 949.	Min	−245 419.	Min	−220 967.
1st Qu	−264 728.	1st Qu	−55 277.1	1st Qu	−52 984.9	1st Qu	−45 230.9
Median	−94 690.2	Median	−2572.99	Median	−5156.78	Median	−1497.8
Mean	−92 109.1	Mean	−1251.77	Mean	−4096.25	Mean	−147.141
3rd Qu	87 497.4	3rd Qu	56 217.4	3rd Qu	47 778.6	3rd Qu	47 327.6
Max	273 814.	Max	268 400.	Max	267 045.	Max	218 209.

5 column 5		6 column 6		7 column 7		8 column 8	
Min	−52 090.5	Min	−2249.95	Min	−2721.42	Min	−2861.63
1st Qu	−9402.93	1st Qu	179.617	1st Qu	−639.375	1st Qu	−661.53
Mean	430.155	Mean	768.857	Mean	−57.5662	Median	−104.336
Median	878.368	Median	803.611	Median	−10.2156	Mean	−83.8895
3rd Qu	10 108.	3rd Qu	1353.85	3rd Qu	500.986	3rd Qu	482.929
Max	43 931.8	Max	3590.84	Max	2968.34	Max	2648.53

```
RecordsSummary[trainingData5, Thread → True]
```

3.3.4 Classification results

Here are the final classification results beginning from the classifiers we built in full cycle (cf4, cf5 and cf6). After that we can also check the previous classifiers trained by seen training data (cf1, cf2 and cf3).

This one below is the one we built using the pipeline and validation set:

```
clResult6 = cf6[testData5];
Short[clResult6]
RecordsSummary[clResult6]
Tally[clResult6]
(*Export["test_labels2_new.csv", clResult6]*)
```

```
{1, 1, 1, 1, 1, 1, -1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, -1, 1, 1, <<1198>>,
 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, -1, 1, -1, 1, 1, 1, 1, -1, 1, 1, 1, 1, 1, 1}
```

1 column 1	
Min	−1
Mean	0.8208
1st Qu	1
3rd Qu	1
Max	1
Median	1

```
{{1, 1138}, {-1, 112}}
```

```
test_labels2_new.csv
```

This one below is the one we built using the Mathematica's classify function and WITHOUT a validation set:

```
clResult5 = cf5[testData5];
Short[clResult5]
RecordsSummary[clResult5]
Tally[clResult5]
```

```
{1, 1, 1, 1, 1, 1, -1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
 <<1213>>, 1, 1, 1, 1, -1, 1, -1, 1, 1, 1, 1, -1, 1, 1, 1, 1, 1, 1}
```

```
  1 column 1
  Min     -1
  Mean    0.8176
{ 1st Qu  1      }
  3rd Qu  1
  Max     1
  Median  1
```

```
{{1, 1136}, {-1, 114}}
```

The below is the one we built using the Mathematica's classify function and with a validation set:

```
clResult4 = cf4[testData5];
Short[clResult4]
RecordsSummary[clResult4]
Tally[clResult4]
(*Export["test_labels_new.csv", clResult4]*)
```

```
{1, 1, 1, 1, 1, 1, -1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, -1, 1, 1, <<1198>>,
 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, -1, 1, -1, 1, 1, 1, 1, -1, 1, 1, 1, 1, 1, 1}
```

```
  1 column 1
  Min     -1
  Mean    0.8144
{ 1st Qu  1      }
  3rd Qu  1
  Max     1
  Median  1
```

```
{{1, 1134}, {-1, 116}}
```

```
test_labels_new.csv
```

```
clResult3 = cf3[testData3];
Short[clResult3]
RecordsSummary[clResult3]
Tally[clResult3]
```

4. Comparisons, Learnings and Workload

So far we only know that cf4, cf5 and cf6 predicts different labels for the test data.

```
clRes = Transpose[{cf5[testData5], cf6[testData5]}];
ct = CrossTabulate[clRes];
MatrixForm[ct]
```

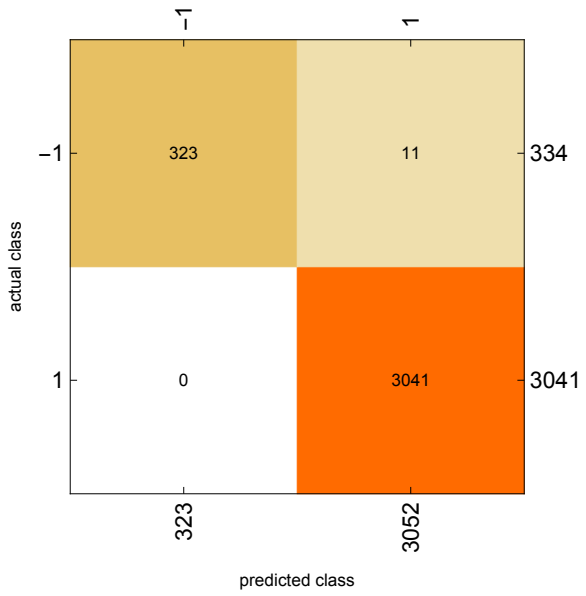
	-1	1
-1	106	8
1	6	1130

```
clRes2 = Transpose[{cf4[testData5], cf6[testData5]}];
ct2 = CrossTabulate[clRes2];
MatrixForm[ct2]
```

	−1	1
−1	109	7
1	3	1131

```
clRes2 = Transpose[{cf1[testData5], cf6[testData5]}];
ct2 = CrossTabulate[clRes2];
MatrixForm[ct2]
```

```
ClassifierMeasurements[cf4, trainingData5, "ConfusionMatrixPlot"]
```



```
ClassifierInformation[cf4]
```

Classifier information

Input type	NumericalVector (length: 8)
Classes	−1, 1
Method	RandomForest
Accuracy	97.0% ± 0.47%
Loss	0.126 ± 0.0050
Single evaluation time	5.06 ms/example
Batch evaluation speed	27.7 examples/ms
Classifier memory	245. kB
Training examples used	3375 examples
Training time	2.47 s

The reason why Random Forest method was used is that it performed the best compared to other methods such as Logistic Regression. Based on the parameters such as accuracy, our classifiers seem to perform good. The question of whether the unseen test data is representative of training data is subject to further examination.

In general we can conclude that the training data included noise that needed to be reduced in dimension space. We can argue that only some features, i.e., 2-5, are decisive, however, it is again subject to further examination whether they are only two vectors or distributed over multiple vectors. Regardless, two-vector dimension reduction and respective classification yielded okay

results. Yet in the full cycle we went with 8 dimensions. cf4 could be a good classifier as it has good classification parameters and also that we used validation set with it.