## **Linear Methods**

We load the precipitation data from a csv file on the harddisk to a DataFrame. Our goal is to predict whether there is some precipitation (rain, snow etc.) on the next day in Pully, getting measurements from different weather stations in Switzerland.

```
md" # Linear Methods
We load the precipitation data from a csv file on the harddisk to a DataFrame.
Our goal is to predict whether there is some precipitation (rain, snow etc.) on the next day in Pully, getting measurements from different weather stations in Switzerland."
```

```
• precipitation = CSV.read(joinpath(@__DIR__, "..", "data", "project",
    "trainingdata.csv"), DataFrame);
```

First we have to prepare our data set by dropping the missing values and split the datas into a train and a test set.

	ABO_radiation_1	ABO_delta_pressure_1	ABO_air_temp_1	ABO_sunshine_1	ABO_win
1	-0.166667	-1.2	-5.68333	0.0	2.08333
2	0.333333	0.2	5.16667	0.0	1.43333
3	16.5	-0.3	6.16667	33.0	0.983333
4	5.33333	-0.6	9.01667	0.0	7.6
5	9.83333	0.3	7.38333	0.0	7.98333
6	25.5	-1.11022e-16	4.36667	48.0	0.483333
7	0.0	-1.0	-1.15	0.0	1.85
8	12.3333	0.8	13.45	20.0	0.516667
9	0.166667	-1.3	4.3	0.0	0.066666
10	0.333333	0.3	2.9	0.0	9.35
: mo	re				
1699	17.3333	0.1	14.9333	28.0	4.48333

```
• p = dropmissing!(precipitation)
```

data\_split (generic function with 1 method)

• p1 = coerce!(p, :precipitation\_nextday => Binary); # with this we tell the computer to interpret the data in column precipitation\_nextday as multi-class data.

```
data1 =
                   ABO_radiation_1 ABO_delta_pressure_1 ABO_air_temp_1
                                                                              ABO_sunshine_1
▶ (train =
                   -0.166667
                                     -1.2
                                                             -5.68333
                                                                              0.0
              1
                   0.333333
              2
                                     0.2
                                                             5.16667
                                                                              0.0
              3
                   16.5
                                     -0.3
                                                             6.16667
                                                                              33.0
                   5.33333
                                     -0.6
                                                             9.01667
                                                                              0.0
              5
                   9.83333
                                     0.3
                                                             7.38333
                                                                              0.0
                   25.5
                                     -1.11022e-16
                                                             4.36667
                                                                              48.0
              6
              7
                                     -1.0
                                                             -1.15
                                                                              0.0
                   0.0
              8
                   12.3333
                                     0.8
                                                             13.45
                                                                              20.0
                   0.166667
                                     -1.3
                                                             4.3
                                                                              0.0
                                     0.3
                   0.333333
                                                             2.9
                                                                              0.0
             10
            ··· more
            1275 0.333333
                                     -0.2
                                                             8.78333
                                                                              0.0
 data1 = data_split(p1)
```

## **Multiple Logistic Regression**

Now we define a supervised learning machine.

	Ground Truth		
Predicted	false	true	
false	710	0	
true	0	565	

```
    confusion_matrix(predict_mode(mach, select(data1.train,
    Not(:precipitation_nextday))),
    data1.train.precipitation_nextday)
```

With our simple features, logistic regression can classify the training data correctly. Let us see how well this works for test data.

```
MLJBase.UnivariateFiniteVector{ScientificTypesBase.Multiclass{2}, Bool, UInt32, Float64

predict(mach, select(data1.test, Not(:precipitation_nextday)))

0.7429245283018868

mean(predict_mode(mach, select(data1.test, Not(:precipitation_nextday))) .==
```

The test accuracy of linear classification is approximately 74%.

	Ground	Truth
Predicted	false	true
false	180	40
true	69	135

data1.test.precipitation\_nextday)

```
    confusion_matrix(predict_mode(mach, select(data1.test,
    Not(:precipitation_nextday))),
    data1.test.precipitation_nextday)
```

Let us evaluate the fit in terms of commonly used losses for binary classification.

```
function losses(machine, input, response)
(loglikelihood = -sum(log_loss(predict(machine, input), response)),
misclassification_rate = mean(predict_mode(machine, input) .!= response),
accuracy = accuracy(predict_mode(machine, input), response),
auc = MLJ.auc(predict(machine, input), response)
)
end;
```

Let's prepare these results for a submission data set. First we have to load the test set, and apply our machine on it. Then we construct our submission data and download it.

• md" Let's prepare these results for a submission data set. First we have to load the test set, and apply our machine on it. Then we construct our submission data and download it."

```
precipitation_test = CSV.read(joinpath(@__DIR__, "..", "data", "project",
    "testdata.csv"), DataFrame);
```

```
pred =
 ▶ MLJBase.UnivariateFiniteVector{ScientificTypesBase.Multiclass{2}, Bool, UInt32, Float64
  pred = predict(mach, precipitation_test)
_pred =
• true_pred = pdf.(pred, true)
   submission = DataFrame(id = 1:1200, precipitation_nextday = true_pred);
 "../data/project/submission_regression.csv"
  CSV.write(".../data/project/submission_regression.csv", submission)
```

## Multiple Logistic Ridge Regression

```
mach1 = machine(LogisticClassifier(penalty = :l2, lambda = 2e-2),
              select(data1.train, Not(:precipitation_nextday)),
              data1.train.precipitation_nextday) |> fit!;
```

```
▶MLJBase.UnivariateFiniteVector{ScientificTypesBase.Multiclass{2}, Bool, UInt32, Float64
predict(mach1, select(data1.train, Not(:precipitation_nextday)))
```

	Ground Truth		
Predicted	false	true	
false	708	3	
true	2	562	

```
confusion_matrix(predict_mode(mach1, select(data1.train,
 Not(:precipitation_nextday))),
                  data1.train.precipitation_nextday)
```

```
▶ MLJBase.UnivariateFiniteVector{ScientificTypesBase.Multiclass{2}, Bool, UInt32, Float64
  predict(mach1, select(data1.test, Not(:precipitation_nextday)))
```

```
0.7382075471698113
  mean(predict_mode(mach1, select(data1.test, Not(:precipitation_nextday))) .==
   data1.test.precipitation_nextday)
```

The test accuracy of linear Ridge classification is approximately 74%.

	Ground Truth		
Predicted	false	true	
false	182	44	
true	67	131	

```
    confusion_matrix(predict_mode(mach1, select(data1.test,
    Not(:precipitation_nextday))),
    data1.test.precipitation_nextday)
```

We see that the test misclassification rate with regularization is lower than in our original fit without regularization. The misclassification rate on the training set is higher. This indicates that unregularized logistic regression is too flexible for our data set.

Let's prepare these results for a submission data set, same steps as the Multiple Logistic Regression.