```
    begin
    using Pkg
    Pkg.activate(joinpath(Pkg.devdir(), "MLCourse")) w
    using CSV, DataFrames, Distributions, Plots, MLJ, MLJLinearModels, Random,
    Statistics, OpenML
    end
```

Linear Methods

We load the precipitation training and test 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_training = CSV.read(joinpath(@__DIR__, "..", "data", "project",
    "trainingdata.csv"), DataFrame);
```

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

First we have to prepare our data set by filling in the missing values with some standard values with the help of FillImputer that fills in the median of all values.

```
    precipitation_training_med = MLJ.transform(fit!(machine(FillImputer(), select(precipitation_training, Not(:precipitation_nextday)))),
    select(precipitation_training, Not(:precipitation_nextday)));
```

```
precipitation_training_med.precipitation_nextday =
precipitation_training[:,:precipitation_nextday];
```

```
    training_data = coerce!(precipitation_training_med, :precipitation_nextday => Binary); # with this we tell the computer to interpret the data in column precipitation_nextday as binary data.
```

Then we standardize our training and test data sets.

```
• fit!(mach_train);
```

	ABO_radiation_1	ABO_delta_pressure_1	ABO_air_temp_1	ABO_sunshine_1	ABO_win
1	-0.750348	-0.495005	-1.51099	-0.362023	-0.39032
2	-0.691886	0.517642	0.124061	-0.362023	-0.54831
3	-0.282652	0.155983	0.79466	-0.362023	-0.56856
4	1.19838	0.155983	0.274757	1.64618	-0.65768
5	-0.185215	0.300647	0.746939	-0.362023	0.051220
6	-0.107266	-0.061013	0.704242	-0.362023	0.950524
7	-0.594449	0.0113189	-0.649513	-0.362023	-0.29715
8	0.418892	0.589974	0.458105	-0.362023	1.04369
9	-0.535987	0.155983	-0.767559	-0.362023	-0.41463
10	0.457866	-0.495005	0.0713174	-0.362023	-0.45919
: mo	re				
3176	1.29582	0.445311	1.59586	1.3419	0.193003

stand_train = MLJ.transform(mach_train, training_data)

```
mach_test = machine(Standardizer(features=[:ZER_sunshine_1, :ABO_sunshine_4,
:ALT_sunshine_4, :CHU_sunshine_4, :SAM_sunshine_4], ignore=true), test_data);
```

fit!(mach_test);

	ABO_radiation_1	ABO_delta_pressure_1	ABO_air_temp_1	ABO_sunshine_1	ABO_wi
1	-0.242687	-1.61917	-0.334016	-0.356409	-0.1824
2	-0.768502	-0.264876	-0.856481	-0.356409	-0.2681
3	-0.242687	0.14141	1.5615	-0.356409	0.25028
4	-0.0284655	0.547697	1.4984	-0.356409	-0.4825
5	-0.242687	1.0217	-0.404688	-0.356409	0.16452
6	-0.223212	0.00598145	-1.09626	-0.356409	0.97145
7	-0.534807	0.683126	-0.755522	-0.356409	-0.5800
8	-0.651655	-2.49945	0.948169	-0.356409	-0.2564
9	-0.671129	-1.00974	0.829542	-0.356409	-0.5215
10	3.20433	-0.874307	-0.366828	3.68604	-0.7008
: mo	re				
1200	0.711572	-0.942021	0.647815	-0.356409	-0.6346

Logistic Regression

stand_test = MLJ.transform(mach_test, test_data)

Lasso regularization

Now we define a supervised learning machine and tune the hyper-parameters. We first try with an interval from 1e-2 to 10 and find a lambda of approximately 4.3.

```
Machine{ProbabilisticTunedModel{Grid,...},...} trained 1 time; caches data
  args:
        Source @249 ← `ScientificTypesBase.Table{AbstractVector{ScientificTypesBase.Conti
    1:
       Source @702 ← `AbstractVector{ScientificTypesBase.Multiclass{2}}`
  begin
       model = LogisticClassifier(penalty = :l1)
       Random.seed! (10)
       self_tuning_model0 = TunedModel(model = model,
                                       resampling = CV(nfolds = 5),
                                       tuning = Grid(goal = 50),
                                       range = range(model, :lambda,
                                               scale = :log,
                                               lower = 1e-2, upper = 10),
                                               measure = auc)
       self_tuning_mach0 = machine(self_tuning_model0, select(stand_train,
                 Not(:precipitation_nextday)),
                 stand_train.precipitation_nextday) |> fit!
 end
```

```
measure = [AreaUnderCurve()], measurement = [0.924738], per_fold = [[... more]]), history =

rep0 = report(self_tuning_mach0)
```

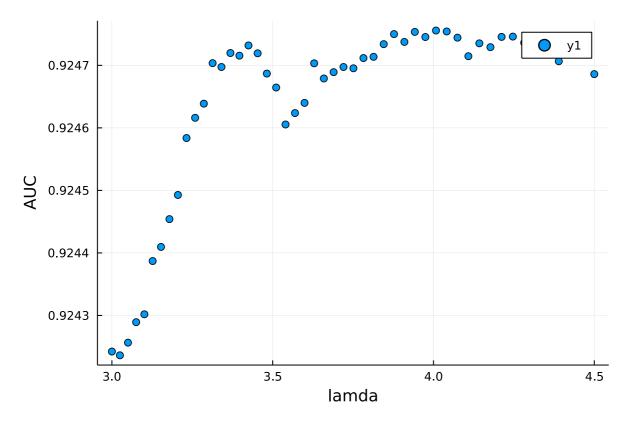
We decided to reduce our interval to find the best lambda.

```
Machine{ProbabilisticTunedModel{Grid,...},...} trained 1 time; caches data
  args:
        Source @914 ← `ScientificTypesBase.Table{AbstractVector{ScientificTypesBase.Cont
    1:
       Source @230 ₽ 'AbstractVector{ScientificTypesBase.Multiclass{2}}'
  begin
       Random.seed! (10)
       self_tuning_model = TunedModel(model = model,
                                      resampling = CV(nfolds = 5),
                                       tuning = Grid(goal = 50),
                                       range = range(model, :lambda,
                                               scale = :log,
                                               lower = 3, upper = 4.5),
                                               measure = auc)
       self_tuning_mach = machine(self_tuning_model, select(stand_train,
                 Not(:precipitation_nextday)),
                 stand_train.precipitation_nextday) |> fit!
 end
```

```
, measure = [AreaUnderCurve()], measurement = [0.924756], per_fold = [[ ··· more]]), hi
```

false,

```
rep = report(self_tuning_mach)
```



```
mach = machine(LogisticClassifier(penalty = :l1, lambda = 4.00775),
select(stand_train, Not(:precipitation_nextday)),
stand_train.precipitation_nextday);
```

```
fit!(mach, verbosity = 2);
```

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

```
pred = predict(mach, stand_test);
```