## GECCO 2017 Industrial Challenge: Monitoring of drinking-water quality









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## Predictors and Response

| Column name | Description  Time of measurement, given in following format: yyyy-mm-dd HH:MM:SS               |  |  |  |  |
|-------------|--|--|--|--|--|
| Time        |  |  |  |  |  |
| Тр          | The temperature of the water, given in °C.   |  |  |  |  |
| cı          | Amount of chlorine dioxide in the water, given in mg/L (MS1)                                   |  |  |  |  |
| pН          | PH value of the water  |  |  |  |  |
| Redox       | Redox potential, given in mV   |  |  |  |  |
| Leit        | Electric conductivity of the water, given in $\mu$ S/cm  |  |  |  |  |
| Trueb       | Turbidity of the water, given in NTU   |  |  |  |  |
| Cl_2        | Amount of chlorine dioxide in the water, given in mg/L (MS2)                                   |  |  |  |  |
| Fm          | Flow rate at water line 1, given in $m^3/h$  |  |  |  |  |
| Fm_2        | Flow rate at water line 2, given in $m^3/h$  |  |  |  |  |
| EVENT       | Marker if this entry should be considered as a remarkable change resp. event given in boolean. |  |  |  |  |





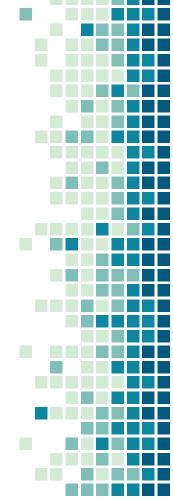
#### Preprocessing

Data have NA values

- Two ways how to deal with them:
  - remove the rows where NA values are present
  - fill with zeros (We recommend this approach)







#### NA values

trainingData <- readRDS("Data/waterDataTraining.RDS") attach(trainingData) summary(trainingData)

| Tp             | cl   | pH   | Redox   | Leit   | Trueb  |
|----------------|--|--|---|--|--|
| Min. : 3.600   | Min. :0.000  | Min. :4.000  | Min. :300.0   | Min. : 0.0   | Min. :0.000  |
| 1st Qu.: 4.100 | 1st Qu.:0.130  | 1st Qu.:8.290  | 1st Qu.:752.0   | 1st Qu.: 212.0   | 1st Qu.:0.013  |
| Median : 4.700 | Median :0.140  | Median :8.390  | Median :758.0   | Median : 216.0   | Median :0.016  |
| Mean : 4.568   | Mean :0.138  | Mean :8.369  | Mean :753.4   | Mean : 220.8   | Mean :0.016  |
| 3rd Qu.: 4.900 | 3rd Qu.:0.140  | 3rd Qu.:8.460  | 3rd Qu.:760.0   | 3rd Qu.: 235.0   | 3rd Qu.:0.019  |
| Max. :10.100   | Max. :0.181  | Max. :8.756  | Max. :894.0   | Max. :2500.0   | Max. :0.500  |
| NA's :11522    | NA's :11520  | NA's :11519  | NA's :11519   | NA's :11519  | NA's :11519  |
| Fm_2           | EVENT  |  |   |  |  |
| Min. : 479.0   | Mode :logical  |  |   |  |  |
| 1st Qu.: 879.0 | FALSE: 120594  |  |   |  |  |
| Median : 942.0 | TRUE :1740   |  |   |  |  |
| Mean : 939.9   | NA's :0  |  |   |  |  |
| 3rd Qu.:1001.0 |  |  |   |  |  |
| Max. :1248.0   |  |  |   |  |  |
| 9 NA's :11519  |  |  |   |  |  |
|                | Min. : 3.600 1st Qu.: 4.100 Median : 4.700 Mean : 4.568 3rd Qu.: 4.900 Max. :10.100 NA's :11522 Fm_2 Min. : 479.0 1st Qu.: 879.0 Median : 942.0 Mean : 939.9 3rd Qu.:1001.0 Max. :1248.0 | Min. : 3.600 Min. :0.000 1st Qu.: 4.100 1st Qu.:0.130 Median : 4.700 Median :0.140 Mean : 4.568 Mean :0.138 3rd Qu.: 4.900 3rd Qu.:0.140 Max. :10.100 Max. :0.181 NA's :11522 NA's :11520 Fm_2 EVENT Min. : 479.0 Mode :logical 1st Qu.: 879.0 FALSE:120594 Median : 942.0 TRUE :1740 Mean : 939.9 NA's :0 3rd Qu.:1001.0 Max. :1248.0 | Min. : 3.600 Min. :0.000 Min. :4.000  1st Qu.: 4.100 1st Qu.:0.130 1st Qu.:8.290  Median : 4.700 Median :0.140 Median :8.390  Mean : 4.568 Mean :0.138 Mean :8.369  3rd Qu.: 4.900 3rd Qu.:0.140 3rd Qu.:8.460  Max. :10.100 Max. :0.181 Max. :8.756  NA's :11522 NA's :11520 NA's :11519  Fm_2 EVENT  Min. : 479.0 Mode :logical  1st Qu.: 879.0 FALSE:120594  Median : 942.0 TRUE :1740  Mean : 939.9 NA's :0  3rd Qu.:1001.0  Max. :1248.0 | Min. : 3.600 Min. :0.000 Min. :4.000 Min. :300.0 1st Qu.: 4.100 1st Qu.:0.130 1st Qu.:8.290 1st Qu.:752.0 Median : 4.700 Median :0.140 Median :8.390 Median :758.0 Mean : 4.568 Mean :0.138 Mean :8.369 Mean :753.4 3rd Qu.: 4.900 3rd Qu.:0.140 3rd Qu.:8.460 3rd Qu.:760.0 Max. :10.100 Max. :0.181 Max. :8.756 Max. :894.0 NA's :11522 NA's :11520 NA's :11519 NA's :11519 Fm_2 EVENT Min. : 479.0 Mode :logical 1st Qu.: 879.0 FALSE:120594 Median : 942.0 TRUE :1740 Mean : 939.9 NA's :0 3rd Qu.:1001.0 Max. :1248.0 | Min. : 3.600 Min. :0.000 Min. :4.000 Min. :300.0 Min. : 0.0 1st Qu.: 4.100 1st Qu.:0.130 1st Qu.:8.290 1st Qu.:752.0 1st Qu.: 212.0 Median : 4.700 Median :0.140 Median :8.390 Median :758.0 Median : 216.0 Mean : 4.568 Mean :0.138 Mean :8.369 Mean :753.4 Mean : 220.8 3rd Qu.: 4.900 3rd Qu.:0.140 3rd Qu.:8.460 3rd Qu.:760.0 3rd Qu.: 235.0 Max. :10.100 Max. :0.181 Max. :8.756 Max. :894.0 Max. :2500.0 NA's :11522 NA's :11520 NA's :11519 NA's :11519 NA's :11519 Fm_2 EVENT Min. : 479.0 Mode :logical 1st Qu.: 879.0 FALSE:120594 Median : 942.0 TRUE :1740 Mean : 939.9 NA's :0 3rd Qu.:1001.0 Max. :1248.0 |





# Monitoring-water system dataset Classification Problem

- Started with three classification algorithms:
  - Logistic Regression(no assumptions, more robust)
  - Linear Discriminant Analysis(LDA)
  - Support Vector Machines(SVM)





### Comparing Accuracy

- 10-fold cross-validation
  - But computing accuracy here does not make sense!
  - Predicting always negative = 99% accuracy!
- Alternatives: precision and recall
- F-measure much better!!!





#### Best algorithm: Logistic Regression

```
logistic.mod <- glm(EVENT ~ Cl_2 + Cl+ pH + Leit + Redox + Trueb + Tp , data = new_data, family = binomial)
predictions1 <- predict(logistic.mod, testing, type = "response")
```

```
Ida.mod <- Ida(EVENT ~ Cl+pH + Leit + Redox + Trueb+Tp, data= training) predictions2 <- predict(Ida.mod, testing, type = "response")
```

```
svm.mod <- svm(EVENT ~ Cl+pH + Leit + Redox + Trueb+Tp, data = training, kernel='linear', cost=0.01)
```

predictions3 <- predict(svm.mod, testing, type="response")</pre>

#### Correlated predictors?

#### Let's improve the model a little bit...

```
t <- trainingData[-c(1,11)] cor(t)
```

```
Tp Cl pH Redox Leit Trueb Cl_2 Fm Fm_2
Tp 1.0000000 0.9488345 0.9554303 0.9445173 0.8988682 0.5289581 0.8462504 0.9380230 0.9231773
Cl 0.9488345 1.0000000 0.9793519 0.9732394 0.9484354 0.5160912 0.9144804 0.9423896 0.9264394
pH 0.9554303 0.9793519 1.0000000 0.9966094 0.9681127 0.5175243 0.9344058 0.9490467 0.9405770
Redox 0.9445173 0.9732394 0.9966094 1.0000000 0.9624241 0.5071290 0.9414415 0.9439183 0.9367541
Leit 0.8988682 0.9484354 0.9681127 0.9624241 1.0000000 0.4991668 0.9405695 0.9058607 0.9028531
Trueb 0.5289581 0.5160912 0.5175243 0.5071290 0.4991668 1.0000000 0.4267623 0.5166251 0.4787937
Cl_2 0.8462504 0.9144804 0.9344058 0.9414415 0.9405695 0.4267623 1.0000000 0.8833198 0.8778636
Fm 0.9380230 0.9423896 0.9490467 0.9439183 0.9058607 0.5166251 0.8833198 1.0000000 0.9199372
Fm_2 0.9231773 0.9264394 0.9405770 0.9367541 0.9028531 0.4787937 0.8778636 0.9199372 1.0000000
```

```
Logistic.mod <<- glm(EVENT ~ Cl_2 + Cl+ pH + Leit + Redox + Trueb + Tp + I(Tp^2+pH^2+Redox^2) + I(pH^2+Leit^2) + I(pH^2+Redox^2), data = new_data, family = binomial)
```

# F1 = 0.579

Logistic Regression

F1 = 0.0756

Linear Discriminant Analysis

F1 = 0.0299

Support Vector Machine



## THANKS!

Any questions?

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