Homeland Security

# TEMPORAL IDENTIFICATION OF CRIMINAL PROFILES AND ACTION PHASES FROM COMMUNICATIONS METADATA DURING SURVEILLANCE INVESTIGATIONS

Benchmark vs. Logistic Regression, Random Forest, Boosted Tree & Neural Network

UC#11— 2024/06 (v5.2) xtractis.ai

## PROBLEM DEFINITION

**GOAL**

**Design an AI-based decision system that accurately identifies risky behavior linked to criminal activities by analyzing communication metadata from surveillance investigations, without accessing the content of telephone calls and rationally predicts dangerous Homeland Security situations.**

**PROS & BENEFITS**

- Identify specific metadata characterizing different criminal activities and enhance expert knowledge by helping intelligence specialists understand the causal relationships between the communication profiles and the roles inside criminal organizations.
- Help intelligence services detect attacks as early as possible and understand the underlying strategy of the criminals in order to consider measures to thwart future attacks.
- Avoid many false alarms thanks to transparent diagnosis.

**REFERENCE DATA**

Source: Confidential data produced by ATOS-BDS-MCS (EVIDEN)

**Variable to Predict**

The model predicts the type of sender profile [**Banal**, **Support**, **Executant**, **Chief**] and the associated temporal phase phase [**P1 Initialization**, **P2 Gathering**, **P3 Planning**, **P4 Execution**] for a total of 10 feasible combinations (10 possible classes):
**BNL | SUP_P2 | SUP_P3 | SUP_P3 | EXEC_P2 | EXEC_P3 | EXEC_P4| CHIEF_P2 | CHIEF_P3 | CHIEF_P4**

**Potential Predictors**

**Each communication is described by 29 to 37 metadata**. These metadata are combined and aggregated over time to obtain **321 potential predictors** [NUM_SMS_2Days: Number of SMS-type communications over the last 2 days, COMVOLUME: Duration of the call in progress...].

**Observations**

**2,492,273 communications within 7 scenarios**. Data are divided into a Learning Dataset for model induction using Training, Validation, and Test Datasets, and an External Test Dataset (involving 6 scenarios) to check the top-model's performance on real data and for benchmarking.

| Learning Dataset: 809,554 cases \| 32.5% (no duplicates)<br>**Training (434,150 \| 53.63%), Validation (160,399 \| 19.81%), Test (215,005 \| 26.56%)** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| BNL | SUP_P2 | SUP_P3 | SUP_P4 | EXEC_P2 | EXEC_P3 | EXEC_P4 | CH_P2 | CH_P3 | CH_P4 |
| 57.84% | 11.83% | 0.95% | 0.16% | 23.15% | 2.19% | 0.37% | 3.17% | 0.30% | 0.04% |

| External Test Dataset: 1,682,719 cases \| 67.5% (no duplicates) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| BNL | SUP_P2 | SUP_P3 | SUP_P4 | EXEC_P2 | EXEC_P3 | EXEC_P4 | CH_P2 | CH_P3 | CH_P4 |
| 47.10% | 16.23% | 0.98% | 0.12% | 28.72% | 1.87% | 0.37% | 4.26% | 0.31% | 0.04% |

**MODEL TYPE** Regression **Multinomial Classification** Binomial Classification Scoring

## XTRACTIS-INDUCED DECISION SYSTEM

☑ **Intelligible Model, Explainable Decisions**

- The top-model is a decision system composed of 12 gradual rules without chaining.
- Each rule uses from 3 to 12 predictors among the 24 variables that XTRACTIS automatically identified as significant (out of the 321 Potential Predictors).
- Only a few rules are triggered at a time to compute the decision.

☑ **High Predictive Capacity** It has a good Real Performance for all 6 External Test Dataset scenarios (on unknown data).

☑ **Ready to Deploy** It computes real-time predictions up to 70,000 decisions/second, offline or online (API).

## XTRACTIS PROCESS

| STEPS | Reference Data | INDUCTION | XTRACTIS Top-Model | New Cases | DEDUCTION | Automated Decision (identify behavior profile & time phase) |
|---|---|---|---|---|---|---|
| SOFTWARE ROBOTS | XTRACTIS® **REVEAL** Delivers the decision system + its Structure & Performance Reports | | | XTRACTIS® **PREDICT** Delivers the decision + the Prediction Report explaining its reasoning | | |

Profile type & time phase

## TOP-MODEL INDUCTION

### INDUCTION PARAMETERS

Powered by:

XTRACTIS® REVEAL v12.2.44349

1. We launch 464 inductive reasoning strategies; each strategy is applied to the same single partition of the learning dataset (53.6% Training / 19.8% Validation / 26.6% Test) to get a reliable assessment of the descriptive and predictive performances, respectively from Training and Validation Datasets.
2. Each strategy thus generates one unitary model called **Individual Virtual Expert** (IVE).
3. Among the 464 induced models, the top-IVE selected is the one that has the best predictive performance, close to its descriptive performance, and with the best intelligibility, i.e., with the fewer predictors and rules.

Total number of induced unitary models
**464 IVEs**

Criterion for the induction optimization
**Average $F_2$-Score**

Validation criterion for the top-model selection
**Average $F_2$-Score**

Duration of the process @ Induction Speed FP64
**35 days** @ 24 Tflops

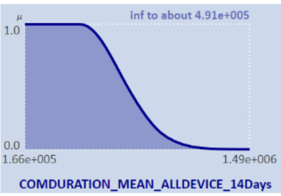
### TOP-MODEL STRUCTURE

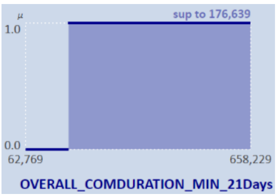
The top-IVE has a very good intelligibility as it has **12 rules** combining **24 predictors**, with 6.3 predictors per rule on average.

Its Structure Report reveals all the internal logic of the decision system and ensures that the model is understandable by the human expert. It is a transparent model that can be audited and certified before deployment to end-users.

#### PREDICTORS

- 24 continuous metadata (out of 321)
- Ranked by impact significance
  (7 strong, 4 medium & 13 weak signals):
  #1 NUM_UNIQUE_USED_DEVICE_SMS_14Days …/…/
  #11 VARPRC_OVERALL_NUM_VOICE_14_21Days …
- Labeled by fuzzy and binary classes
  Examples: **binary interval** “sup to 176,639”;
  **fuzzy interval** “inf to about 4.91e+005”




#### RULES

- 12 connective fuzzy rules without chaining (aggregated into 10 disjunctive fuzzy rules)
- 3 to 12 predictors per rule (on average, 6.3 predictors per rule)
- Example: **fuzzy rule R6** uses 4 predictors and concludes “EXEC_P2” (Profile *Executant*, Phase *Grouping*). 11 other fuzzy rules complete this model.

| | | | |
|---|---|---|---|
| IF | COMDURATION_MEAN_ALLDEVICE_14D | IS | inf to ~4.91e+005 |
| AND | NUM_UNIQUE_USED_DEVICE_1D | IS | sup to ~1.99 |
| AND | OVERALL_COMDURATION_MIN_21D | IS | sup to 176,639 |
| AND | VARPRC_OVERALL_NUM_SMS_3_7D | IS | sup to ~-57.0 |
| THEN | Sender Profile_Phase | IS | EXEC_P2 |

*Literally, intercepted communication is that of an EXECUTANT in Gathering Phase if his mean duration of communication, during the last 14 days, is inferior to 8’11”, and his number of different devices used, during the last 24h, is 2 or more, and the group’s minimum duration of communication, during the last 21 days, is superior to 2’57”, and the relative change in group’s number of SMS, between the last 3 and the last 7 days, is superior to -57%.*

### TOP-MODEL PERFORMANCE

The top-IVE performances, measured in Training / Validation / Test, then in External Test for each of the 6 scenarios, guarantee the model’s predictive and real performances.

| Performance Type | DESCRIPTIVE | PREDICTIVE | REAL | REAL |
|---|---|---|---|---|
| Dataset | 53.6% Training | 19.8% Validation | 26.6% Test | External Test |
| Average $F_2$-Score | 92.37% | 90.40% | 89.82% | 87.23% |
| Classification Error | 1.41% | 1.56% | 1.06% | 0.64% |

# EXPLAINED PREDICTIONS FOR 2 UNKNOWN CASES

Powered by: XTRACTIS® PREDICT v12.2.44349

**CASE**
(from the External Test Dataset, i.e., not included in the Learning Dataset)

**DEDUCTIVE INFERENCE OF RULES**

**AUTOMATED DECISION**

## ihfgwmqida_2014-05-23 16:17:47.166

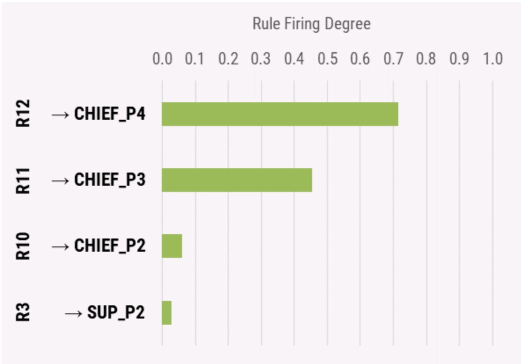
| actual value = CHIEF_P4 | |
|---|---|
| COMDURATION_MEAN_7D | 1.83e+005 |
| NUM_UNIQUE_TMSI_RECEIVER_SMS_3D | Missing Value |
| NUM_UNIQUE_USED_DEVICE_SMS_14D | 6.00 |
| NUM_VOICE_ALLDEVICE_1D | 4.0 |
| ... | ... |
| OVERALL_COMDURATION_MIN_21D | 80,186 |
| VARPRC_NUM_UNIQUE_TMSI_RECEIVER_1_2D | 0.0 |
| VARPRC_NUM_VOICE_ALLDEVICE_7_14D | -61.2 |
| VARPRC_OVERALL_NUM_SMS_1_2D | -49.7 |
| VARPRC_OVERALL_NUM_VOICE_7_14D | -50.7 |

Real Time

For this communication, 4 rules are triggered:

**R12** at 0.715, **R11** at 0.453, **R10** at 0.061 and **R3** at 0.027

The 8 other rules are not activated.




NUMBER OF TRIGGERED RULES
4 / 12

FUZZY PREDICTION
{ CHIEF_P4 | 0.715,
CHIEF_P3 | 0.453,
CHIEF_P2 | 0.061,
SUP_P2 | 0.027 }

FINAL PREDICTION
{ CHIEF_P4 }

The system delivers the correct diagnosis compared to that given by the intelligence expert:

**Profile CHIEF, Phase EXECUTION**

## wavzigquktqy_2013-09-24 21:54:39.903

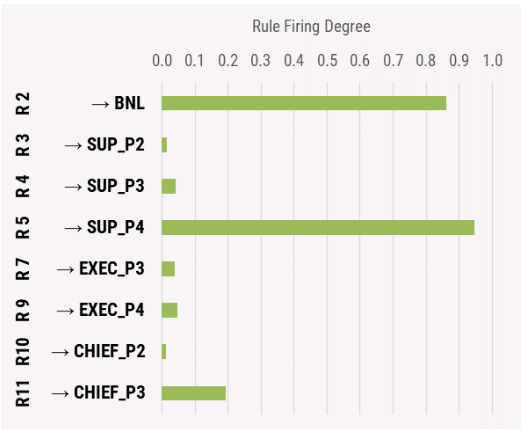
| actual value = SUP_P4 | |
|---|---|
| COMDURATION_MEAN_7D | 3.74E+05 |
| NUM_UNIQUE_TMSI_RECEIVER_SMS_3D | Missing Value |
| NUM_UNIQUE_USED_DEVICE_SMS_14D | 2.00 |
| NUM_VOICE_ALLDEVICE_1D | 2.0 |
| ... | |
| OVERALL_COMDURATION_MIN_21D | 64,285 |
| VARPRC_NUM_UNIQUE_TMSI_RECEIVER_1_2D | 0.0 |
| VARPRC_NUM_VOICE_ALLDEVICE_7_14D | -33.3 |
| VARPRC_OVERALL_NUM_SMS_1_2D | -46.6 |
| VARPRC_OVERALL_NUM_VOICE_7_14D | -50.6 |

Real Time

For this communication, 8 rules are triggered:

**R5** at 0.946, **R2** at 0.860, **R11** at 0.194...

The 4 other rules are not activated.




NUMBER OF TRIGGERED RULES
8 / 12

FUZZY PREDICTION
{ SUP_P4 | 0.946
BNL | 0.860,
CHIEF_P3 | 0.194,
EXEC_P4 | 0.048,
SUP_P3 | 0.041
EXEC_P3 | 0.039
SUP_P2 | 0.014
CHIEF_P2 | 0.013 }

FINAL PREDICTION
{ SUP_P4 }

The system delivers the correct diagnosis compared to that given by the intelligence expert, although it considered that it could also be a Banal behavior with a closer possibility:

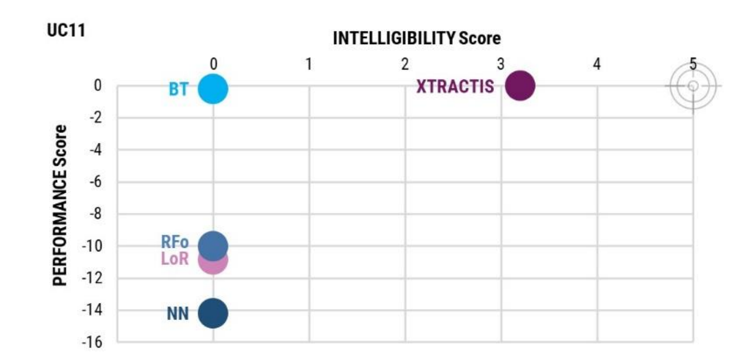
**Profile SUPPORT, Phase EXECUTION**

# TOP-MODELS BENCHMARK

| | | XTRACTIS | LOGISTIC REGRESSION | RANDOM FOREST | BOOSTED TREE | NEURAL NETWORK |
|---|---|---|---|---|---|---|
| MODELING PARAMETERS | MODELS RELEASE | 2023/01 | 2023/01 | 2023/01 | 2023/01 | 2023/01 |
| | ALGORITHM VERSION | XTRACTIS **REVEAL** 12.2.44349 | Python 3.9 \| Scikit-Learn 1.3.0 | Python 3.9 \| LightGBM 3.3.2 | Python 3.9 \| LightGBM 3.3.2 | Python 3.9 \| TensorFlow 2.10.0 \| Keras 2.10.0 |
| | CROSS-VALIDATION TECHNIQUE | All explored strategies for all algorithms use the same single-split of the Learning Dataset: 60% Training \| 20% Validation \| 20% Test | | | | |
| | NUMBER OF EXPLORED STRATEGIES(1) | 464 induction strategies | 1,000 data analysis strategies | 1,000 ML strategies | 1,000 ML strategies | 1,000 ML strategies |
| | TOP-MODEL SELECTION(2) | Top-IVE among 464 IVEs | Top-IVE among 1,000 IVEs | Top-IVE among 1,000 IVEs | Top-IVE among 1,000 IVEs | Top-IVE among 1,000 IVEs |

| | | XTRACTIS | LOGISTIC REGRESSION | RANDOM FOREST | BOOSTED TREE | NEURAL NETWORK |
|---|---|---|---|---|---|---|
| TOP-MODEL STRUCTURE | NUMBER OF PREDICTORS (out of 321 Potential Predictors) | **24** | **321** | **299** | **313** | **321** |
| | AVERAGE NUMBER OF PREDICTORS PER RULE OR EQUATION | **6.3** per rule | **321.0** per equation | **8.3** per rule | **6.1** per rule | **117.6** per equation |
| | STRUCTURE OF THE DECISION SYSTEM | **12** fuzzy rules without chaining (aggregated into 10 disjunctive fuzzy rules)<br>Only a few rules are triggered at a time to compute a decision | **10** linear equations | **500** trees without chaining<br>**20,216** binary rules | **10** chains of **309** trees each<br>**49,797** binary rules<br>Tree #N corrects the error of the N-1 previous trees | **2** hidden layers \| **22** hidden nodes<br>**32** equations<br>22 unintelligible synthetic variables |

| TOP-MODEL SCORES | | Random(3) | XTRACTIS | LoR | RFo | BT | NN |
|---|---|---|---|---|---|---|---|
| | **INTELLIGIBILITY Score(4)** | | **3.20** | **0.00** | **0.00** | **0.00** | **0.00** |
| | IVE Real Perf. (Average $F_2$-Score) in Test | | 89.82 | 78.89 | 77.83 | 89.54 | 84.20 |
| | **Gap to Leader in Test** | | **0.00** | **-10.93** | **-11.99** | **-0.28** | **-5.62** |
| | IVE Real Perf. (Average $F_2$-Score) in External Test | 7.79% | 87.23 | 76.46 | 79.19 | 87.14 | 64.47 |
| | **Gap to Leader in External Test** | | **0.00** | **-10.77** | **-8.04** | **-0.09** | **-22.76** |
| | IVE Average Real Performance | | 88.53 | 77.68 | 78.51 | 88.34 | 74.34 |
| | **PERFORMANCE Score(4)** | | **0.00** | **-10.85** | **-10.02** | **-0.18** | **-14.19** |




(1) For all algos: on the same Learning Dataset. All Models are optimized according to their Validation Average $F_2$-Score.
(2) All top-models are selected according to their Validation Average $F_2$-Score while checking that it remains close to their Training Average $F_2$-Score.
(3) Baseline performances that models must exceed to perform better than chance (P-value = 0.001; 100,000 models generated by random permutation of the output values). The value of each performance criterion is generally achieved by a different random model.
(4) See Appendices for explanations and detailed results. Performance Scores are calculated on all available unknown data.

More Use Cases:
xtractis.ai/use-cases/

# APPENDIX 1 — Calculation of the Intelligibility × Performance

| | | |
|---|---|---|
| AI Technique #i | $T_i$ | $i \in [1 ; n]$<br>n = number of AI Techniques benchmarked in terms of data-driven modeling = 5 |
| Benchmark #k | $B_k$ | $k \in [1 ; p]$<br>p = number of Benchmarks for the Use Case ∈ {1, 2, 3} |

*Remarks*:

- In case of a small number of reference data, a CVE model (College of Virtual Experts) is generated by each explored strategy of $T_i$, generally via an N×K-fold cross validation. In this case, a Benchmark is led with the top-CVE on the External Test Dataset (ETD, composed of unknown reference cases). Then, a top-IVE model (Individual Virtual Expert) is generated from the top-CVE, through the XTRACTIS® reverse-engineering process, or for the other $T_i$, by applying the top-strategy, which has generated the top-CVE, on the Training and Validation Datasets. And a second Benchmark is led with this top-IVE on the same ETD.
- In case of a huge number of reference data, an IVE is generated by each explored strategy of $T_i$, via a 1-split validation. In this case, Benchmarks are led with the top-IVE on the Test Dataset (TD, composed of unknown reference cases) and on the available ETDs.
- Each Benchmark uses the latest versions of the following algorithms available at the date of the benchmark. XTRACTIS®: REVEAL; Logistic Regression: Python, Scikit-Learn; Random Forest & Boosted Tree: Python, LightGBM; Neural Network: Python, TensorFlow, Keras.
- Each $B_k$ uses exactly the same TD and ETD for each $T_i$ model.
- No Regression models can be obtained by Logistic Regression. So, this Data Analysis technique is benchmarked only for Classification or Scoring problems.
- The Holy Grail for critical AI-based decision systems is to obtain a model with the highest Performance and the highest Intelligibility scores (top-right corner of the graph).

## PERFORMANCE Score

For each $B_k$, we calculate the values of the Performance Criterion (PC) on the same ETD for all the $T_i$ top-CVEs; and on the same TD and ETDs for all the $T_i$ top-IVEs. The PC is: RMSE in percentage for a Regression; $F_1$-Score for a Binomial Classification; Average $F_1$-Score or Average $F_2$-Score for a Multinomial Classification; Gini index for a Scoring.
Then, we compare the value of the PC of each $T_i$ top-CVE (resp. top-IVE) to the best value of this PC reached by the best $T_i$ top-CVE (resp. top-IVE) on ETD (resp. on TD and ETDs).

For Regression, we calculate for each $T_i$ top-model (CVE and IVE): $PS(T_i, B_k) = Best\_PC(B_k) - PC(T_i, B_k)$.

For Classification and Scoring, we calculate for each $T_i$ top-model: $PS(T_i, B_k) = PC(T_i, B_k) - Best\_PC(B_k)$.

Performance Score of $T_i$

$$\boxed{PS(T_i) = \text{Mean}\left(PS(T_i, B_k)\right)_{k \in [1 ; p]}}$$

*Remark:*

- Each PS varies theoretically from -100 (Lowest Score) to 0 (Highest Score), but practically between -50 and 0.

## INTELLIGIBILITY Score

We consider the $T_i$ top-IVE. Its Intelligibility Score $IS(T_i)$ is valued from 0.00 to 5.00 regarding the structure of the model: number of predictors, classes, rules, equations, trees, synthetic variables, modalities to predict for classifications (or numeric variables to predict for regressions or scoring). The more compact the model, the higher its IS.

The IS of each $T_i$ is obtained by accumulating the following five penalty values to the ideal IS value of 5.00 (each penalty has a null or a negative value):

- Penalty 1 (logarithmic penalty regarding the number of predictors):

$$Pen1(T_i) = \min(0\,, 1 - \log_{10} number\ of\ predictors)$$

*Examples:* *Pen1 = 0.00 for up to 10 predictors*
*Pen1 = –3.00 for 10.000 predictors*

- Penalty 2 (linear penalty regarding the average number of rules or equations per modality to predict):

$$Pen2(T_i) = \min\left(0\,, 0.01 - \frac{average\ number\ of\ rules\ or\ equations\ per\ modality\ to\ predict}{100}\right)$$

*Examples:* *Pen2 = 0.00 for 1 rule or equation per modality to predict on average*
*Pen2 = –3.00 for 301 rules or equations per modality to predict on average*

- Penalty 3 (linear penalty regarding the average number of predictors per rule or equation):

$$Pen3(T_i) = \min\left(0\,, \frac{9 - 3 \times average\ number\ of\ predictors\ per\ rule\ or\ equation}{7}\right)$$

*Examples:* *Pen3 = 0.00 for up to 3.0 predictors per rule or equation on average*
*Pen3 = –3.00 for 10.0 predictors per rule or equation on average*

- Penalty 4 (linear penalty regarding the number of trees per chain, here for BT only):

$$Pen4(T_i) = \min(0\,, 1 - number\ of\ trees\ per\ chain)$$

*Examples:* *Pen4 = 0.00 for 1 tree per chain*
*Pen4 = –3.00 for 4 trees per chain*

- Penalty 5 (maximum penalty due to unintelligibility of synthetic variables, here for NN only):

$$Pen5(T_i) = -5$$

Intelligibility Score of $T_i$

$$\boxed{IS(T_i) = \max(0.00\,, 5.00 + (Pen1+Pen2+Pen3+Pen4+Pen5))}$$

*Remarks:*

- For the difference between the Intelligibility and the Explainability of a model, please see the XTRACTIS® Brochure, page 7.
- The real complexity of the process/phenomenon under study is intrinsic, i.e., it could not be reduced or simplified, but only discovered; thus, the top-model will be complex if the process/phenomenon turns out to be complex [Zalila 2017]. Consequently, for some complex process/phenomenon, IS can be equal to 3.00 or less, even if Ti natively produces intelligible models (XTRACTIS, Random Forest).
- For similar structures, the Boosted Tree model is always less intelligible than the Random Forest one, as it is composed of chains of trees, instead of a college of trees (see Penalty 4).
- Neural Network model has always the lowest IS of 0.00, because it uses synthetic unintelligible variables (hidden nodes) in addition to all the potential predictors (see Penalty 5).

## APPENDIX 2 — Use Case Results (all Performance criteria of all Top-Models)

| Performance Criterion | Classification Error | Min. Sensitivity | Average Sensitivity | Min. PPV | Average PPV | **Average $F_2$-Score** | Weighted Av. $F_2$-Score | Refusal |
|---|---|---|---|---|---|---|---|---|
| **RANDOM MODEL** | | | | | | | | |
| *Number of Random Permutations (P-value) = 100,000 (0.001)* | | | | | | | | |
| *Performance against chance* | *81.55%* | *0.37%* | *7.79%* | *0.37%* | *7.79%* | ***7.79%*** | *18.45%* | |
| **XTRACTIS TOP-MODEL** | | | | | | | | |
| Descriptive Performance (Training) | 1.41% | 74.22% | 93.01% | 56.22% | 92.07% | 92.37% | 98.59% | 0 (0.00%) |
| Predictive Performance (Validation) | 1.56% | 51.21% | 89.63% | 79.06% | 94.84% | 90.40% | 98.42% | 0 (0.00%) |
| Real Performance (Test) | 1.06% | 60.97% | 90.75% | 49.44% | 90.87% | **89.82%** | 98.92% | 2 (0.00%) |
| Real Performance (External Test for 6 scenarios) | 0.64% | 46.37% | 87.48% | 54.63% | 87.85% | **87.23%** | 99.36% | 0 (0.00%) |
| **LOGISTIC REGRESSION TOP-MODEL** | | | | | | | | |
| Descriptive Performance (Training) | 0.91% | 76.09% | 93.11% | 91.11% | 97.84% | 93.93% | 99.09% | |
| Predictive Performance (Validation) | 4.21% | 54.57% | 82.36% | 29.04% | 82.37% | 80.44% | 95.74% | |
| Real Performance (Test) | 2.45% | 44.69% | 84.64% | 22.34% | 81.36% | **78.89%** | 97.52% | |
| Real Performance (External Test for 6 scenarios) | 8.11% | 44.91% | 80.62% | 26.85% | 80.06% | **76.46%** | 91.75% | |
| **RANDOM FOREST TOP-MODEL** | | | | | | | | |
| Descriptive Performance (Training) | 0.31% | 93.49% | 98.29% | 80.48% | 95.06% | 97.58% | 99.70% | |
| Predictive Performance (Validation) | 8.42% | 30.47% | 80.66% | 24.15% | 73.28% | 76.35% | 91.82% | |
| Real Performance (Test) | 7.18% | 17.76% | 85.56% | 11.63% | 68.95% | **77.83%** | 93.14% | |
| Real Performance (External Test for 6 scenarios) | 12.20% | 55.29% | 86.68% | 20.55% | 68.28% | **79.19%** | 88.29% | |
| **BOOSTED TREE TOP-MODEL** | | | | | | | | |
| Descriptive Performance (Training) | 0.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | |
| Predictive Performance (Validation) | 2.92% | 30.28% | 84.92% | 66.63% | 91.97% | 84.91% | 96.97% | |
| Real Performance (Test) | 2.08% | 42.36% | 89.65% | 59.03% | 94.12% | **89.54%** | 97.80% | |
| Real Performance (External Test for 6 scenarios) | 3.93% | 49.74% | 87.26% | 57.03% | 92.97% | **87.14%** | 95.97% | |
| **NEURAL NETWORK TOP-MODEL** | | | | | | | | |
| Descriptive Performance (Training) | 0.64% | 78.52% | 95.67% | 82.20% | 95.59% | 95.55% | 99.35% | |
| Predictive Performance (Validation) | 2.90% | 56.64% | 87.76% | 77.30% | 89.45% | 87.83% | 97.06% | |
| Real Performance (Test) | 1.81% | 61.68% | 87.57% | 33.50% | 82.59% | **84.20%** | 98.16% | |
| Real Performance (External Test for 6 scenarios) | 18.09% | 23.19% | 69.84% | 32.24% | 70.28% | **64.47%** | 81.43% | |