

COREALIS Final Conference

COREALIS Asset Management Predictor

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□ Preventive vs Predictive Maintenance:

- **Preventive Maintenance**: Engineers inspect vehicles every couple of months. This method is costly and does not capture asset-specific conditions (for e.g. rides per day, occupancy level, weather conditions, etc.).
- **Predictive Maintenance (PdM)** solutions takes into account the operating conditions of vehicles by leveraging data collected from individual assets to predict failures in future.

Overview:

- Data Collection: Equipment Data and Maintenance Data
- **PdM Platform**: Preprocessing and Training AI Model
- Outputs: Schedules, Overview of Assets and Purchase Optimization

Customer Value:

- Reduced Asset Downtime,
- Reduced maintenance and repair costs,
- Optimize spare parts inventory











□ Market Size (General):

 Analysts consensus on growth rate at 25-30% CAGR in 2020-2025 period (Allied Market Research, Market Expert 24, ReportBuyer), but have diverse market size estimates (\$15-30B)

PdM Solutions:

- Predictive Maintenance is an imbalanced classification problem where number of part failures is much smaller than predominant normal working parts.
- To the best of our knowledge, PdM solutions (from Bosch, SAP, Huwaei, IBM and SAP) relies on statistical analysis.
- Their solutions does not relies on advanced machine learning algorithms tailored for imbalanced classification tasks.









IJCNN 2020

- **BRIGHT** is NEC's Ensemble Learning Technology:
 - Combine many weak learners to build a more efficient learner
 - Many specialized weak learners can beat a strong one
 - That's because "strong" learners (singletons) model the variable in a wide set of conditions, sacrificing memory of rare events to work in general

□ Meta-Learning

- learning how learners perform in which situation
- A Meta-Learner learns from the behavior of other learners (= base learners)

□ BRIGHT DAMVI*: Meta-learning for imbalanced data classification

- Learns a diversity-aware weighted majority vote classifier over the base classifiers
- Delivers benefits in terms of F1-score and Average Precision especially in four main applications: predictive maintenance tasks, credit fraud detection, medical diagnosis and webpage classification.
- Performs well even for highly imbalanced classification tasks (< 4% positive class examples).

*Diversity-Aware Weighted Majority Vote Classifier for Imbalanced Data

*Anil Goyal and Jihed Khiari, "Diversity-Aware Weighted Majority Vote Classifier for Imbalanced Data", The International Joint Conference on Neural Networks (IJCNN), 2020





Technology Description (BRIGHT DAMVI)

Base Classifiers: Learn a set of base classifiers corresponding to K bootstrapped samples

- □ Reweighing of Examples: DAMVI increases the weights of positive examples (minority class) which are "hard" to classify with uniformly weighing of classifiers.
- □ Learning Diversity-Aware Weighted Majority Vote: Learned base classifiers are combined using diversityaware weighted majority vote:

$$H(x) = \sum_{k=1}^{K} Q(k) \cdot h_k(x)$$

where, $h_k(x)$ is a base learner corresponding to subsampled data D_K and Q(k) is the weight over base learner.









	Datasets				
	#Attributes $#$ Examples IR				
Webpage	300	34780	3.03		
Mammography	6	11183	2.32		
Scania	170	60000	1.67		
Protein Homo	74	145751	0.9		
Credit Fraud	30	284807	0.17		
PCT Data	17	816099	0.02		

- □ DAMVI performs best on all datasets in terms of F1-score and for 5 out of 6 datasets in terms of Average Precision.
- □ DAMVI performs significantly better on PCT dataset with lowest imbalance ratio of 0.02.



			F1-score	9		IJCNN 2020
	Webpage	Mammography	Scania	Protein Homo	Credit Fraud	PCT Data
S-DT	.5062±.028↓	$.5198 \pm .009^{\downarrow}$.5848±.011↓	$.5278 \pm .005^{\downarrow}$	$.5610 \pm .016^{\downarrow}$.8793±.011↓
R-DT	.4705±.021↓	.6053±.043↓	$.6256 \pm .019^{\downarrow}$	$.7290 \pm .017^{\downarrow}$	$.7556 \pm .013^{\downarrow}$	$.9715 \pm .002^{\downarrow}$
A-DT	.4693±.019 [↓]	$.4978 \pm .034^{\downarrow}$	$.5807 \pm .020^{\downarrow}$	$.5259 {\pm} .019^{\downarrow}$	$.5653 \pm .027^{\downarrow}$	$.8830 \pm .009^{\downarrow}$
R-BG	.4620±.016↓	$.6145 \pm .026^{\downarrow}$.6845±.014↓	.7849±.021↓	.7703±.020↓	$.9691 \pm .001^{\downarrow}$
S-BG	$.6134 \pm .017^{\downarrow}$	$.5391 \pm .017^{\downarrow}$.6493±.009↓	$.6771 \pm .009^{\downarrow}$.6839±.024 [↓]	$.9430 \pm .006^{\downarrow}$
A-BG	.4804±.021↓	$.5169 \pm .011^{\downarrow}$	$.6269 \pm .007^{\downarrow}$	$.6346 \pm .013^{\downarrow}$	$.6819 \pm .030^{\downarrow}$	$.9312 \pm .004^{\downarrow}$
BB	.3445±.001↓	$.4465 \pm .030^{\downarrow}$	$.4317 \pm .005^{\downarrow}$	$.4275 \pm .008^{\downarrow}$	$.1376 \pm .006^{\downarrow}$.8014±.006↓
BRF	.4098±.010↓	$.3659 \pm .014^{\downarrow}$.3822±.004↓	$.4027 \pm .009^{\downarrow}$	$.1255 \pm .016^{\downarrow}$	$.2943 \pm .007^{\downarrow}$
EE	.4678±.011↓	$.2534 \pm .002^{\downarrow}$.4096±.006↓	$.3350 \pm .003^{\downarrow}$	$.0922 \pm .007^{\downarrow}$.0881±.001↓
DAMVI	.7996 ±.011	$.6661 \pm .023$	$.7289 \pm .011$.8067±.009	$.8495 \pm .019$	$.9816 \pm .001$

Average Precision

	Webpage	Mammography	Scania	Protein Homo	Credit Fraud	PCT Data
S-DT	.2794±.023↓	$.2919 \pm .010^{\downarrow}$	$.3526 \pm .014^{\downarrow}$	$.3153 \pm .005^{\downarrow}$	$.3482 \pm .016^{\downarrow}$.7785±.001↓
R-DT	$.3008 \pm .016^{\downarrow}$	$.3811 \pm .054^{\downarrow}$.3994±.024 [↓]	$.5347 \pm .025^{\downarrow}$	$.5728 \pm .020^{\downarrow}$.9447±.005↓
A-DT	$.2481 \pm .014^{\downarrow}$	$.2740 \pm .034^{\downarrow}$.3483±.023↓	$.3112 \pm .019^{\downarrow}$	$.3516 \pm .030^{\downarrow}$.7851±.016↓
R-BG	.4944±.010↓	$.7011 \pm .021$	$.8097 \pm .016^{\downarrow}$	$.8495 {\pm} .016$	$.8120 \pm .030^{\downarrow}$	$.9875 {\pm}.001$
S-BG	.6219±.028↓	$.6971 \pm .025^{\downarrow}$	$.7275 \pm .019^{\downarrow}$	$.8424 \pm .013$	$.8135 \pm .027^{\downarrow}$.9863±.001↓
A-BG	.4400±.024↓	$.6261 \pm .036^{\downarrow}$.6712±.018↓	$.8276 \pm .016$. <i>813</i> 7±.035↓	.9847±.005↓
BB	.6302±.034↓	$.6644 \pm .037^{\downarrow}$.6745±.024↓	$.8359 {\pm} .018$.7516±.048↓	.9849±.001↓
BRF	.6930±.022↓	$.6782 \pm .023$.6877±.016↓	$.8549 {\pm} .014$.7615±.047↓	$.6976 \pm .010^{\downarrow}$
EE	$.6969 \pm .038^{\downarrow}$	$.5967 \pm .043^{\downarrow}$.7558±.014 [↓]	$.8561 \pm .012$	$.7672 \pm .025^{\downarrow}$.0790±.001↓
DAMVI	.8331±.013	$.7142 \pm .039$	$.8335 \pm .007$	$.8267 \pm .013$.8373±.027	.9976±.001







Web Interface Step 1:

□ User can check if there any learned exists model for a particular part (from past).

Step 2:

□ User can validate if the required data for training and testing are stored desired at location or not.

COREALIS Predictor				COREALIS Predictor	
Asset Management F	Predictor		Asse	et Management Prec	dictor
ome Validate Train Predict		Home	Validate	Train Predict	
Check Available Mod	lel	Che	ck the availa	ability of required data for tra	ining and testing
Part ID: P14143213	3/1			Truck Id List	
Check model				Training Telemetry Data	
				Training Maintenance Data	
				Testing Telemetry Data	
	NEC		COREALIS	PCT	NEC
resent software implements NEC Laboratories Europe GmbH BRIG	HT predictive analytics technology, BRIGHT	The present	software implement	s NEC Laboratories Europe GmbH BRIGHT pred	ictive analytics technology. E

software implements NEC Laboratories Europe GmbH BRIGHT predictive analytics technology. BRIGHT tics algorithms and software were adapted for usage in the EU COREALIS project (EU GRANT Nr 768994) to obtain this software release. This software is provided to designated COREALIS consortium members under the terms and conditions of the COREALIS Consortium Agreement (see section 9.3 Access Rights for implementation)

COREALIS Predictor



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Web Interface

Step 3:

Train the machine learning models for a particular part using prediction horizon and number of CPUs as input tomorrow.

Step 4:

□ Failures predictions (along with probability) are saved in respective folder in csv file.

Asset Management Predictor						
Home	Validate	Train	Predict			
	r	rain Macl	hine Lear	ning Model		
	Predict	ion Horizo	on (Days):	14		
	Part ID	:		P14143213/1		
	CPUs (Parallel T	raining):	2		
			Train ML Mod	el		
ç	COREALIS		≁СТ	,	NEC	
The present	software implements	NEC Laborator	ies Europe Gm	bH BRIGHT predictive anal	ytics technology. BRIGHT	

COREALIS Predictor

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COREALIS Predictor						
	Asse	t Man	agement P	redictor		
Home	Validate	Train	Predict			
		Pr	edict Failures			
	Par	t ID:	P14143213/	1		
			Predict Failures			
			→PCT	NEC		
1	ERCER DE THE RUTURE					

The present software implements NEC Laboratories Europe GmbH BRIGHT predictive analytics technology. BRIGHT predictive analytics algorithms and software were adapted for usage in the EU COREALIS project (EU GRANT Nr 768994) to obtain this software release. This software is provided to designated COREALIS consortium members under the terms and conditions of the COREALIS Consortium Agreement (see section 9.3 Access Rights for implementation)







THANK YOU FOR YOUR ATTENTION



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