

Importando Bibliotecas

```
!pip install --use-deprecated=legacy-resolver pycaret[full]
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: pycaret[full] in /usr/local/lib/python3.8/dist-packages (2.3.10)
Requirement already satisfied: mlflow in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (2.1.1)
Requirement already satisfied: nltk in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (3.7)
Requirement already satisfied: yellowbrick>=1.0.1 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (1.5)
Requirement already satisfied: cufflinks>=0.17.0 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.17.3)
Requirement already satisfied: pandas-profiling>=2.8.0 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (3.6.6)
Requirement already satisfied: mlxtend>=0.17.0 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.21.0)
Requirement already satisfied: Boruta in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.3)
Requirement already satisfied: pyyaml<6.0.0 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (5.4.1)
Requirement already satisfied: joblib in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (1.2.0)
Requirement already satisfied: kmodes>=0.10.1 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.12.2)
Requirement already satisfied: imbalanced-learn==0.7.0 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.7.0)
Requirement already satisfied: spacy<2.4.0 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (2.3.9)
Requirement already satisfied: lightgbm>=2.3.1 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (3.3.5)
Requirement already satisfied: pyod in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (1.0.7)
Requirement already satisfied: umap-learn in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.5.3)
Requirement already satisfied: wordcloud in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (1.8.2.2)
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Requirement already satisfied: IPython in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (7.9.0)
Requirement already satisfied: numba<0.55 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.54.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (3.2.2)
Requirement already satisfied: pyLDAvis in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (3.3.1)
Requirement already satisfied: seaborn in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.11.2)
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Requirement already satisfied: scipy<=1.5.4 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (1.5.4)
Requirement already satisfied: ipywidgets in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (7.7.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (1.3.5)
Requirement already satisfied: gensim<4.0.0 in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (3.6.0)
Requirement already satisfied: scikit-plot in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.3.7)
Requirement already satisfied: optuna>=2.2.0; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (5.5.0)
Requirement already satisfied: interpret<=0.2.4; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.2.4)
Requirement already satisfied: azure-storage-blob; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (12.14.1)
Requirement already satisfied: gradio; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (3.18.0)
Requirement already satisfied: tune-sklearn>=0.2.1; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (3.1.0)
Requirement already satisfied: psutil; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (5.4.8)
Requirement already satisfied: ray[tune]>=1.0.0; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (2.2.0)
Requirement already satisfied: catboost>=0.23.2; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.4.5)
Requirement already satisfied: scikit-optimize>=0.8.1; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (0.9.0)
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Requirement already satisfied: google-cloud-storage; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (2.7.0)
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Requirement already satisfied: xgboost>=1.1.0; extra == "full" in /usr/local/lib/python3.8/dist-packages (from pycaret[full]) (1.7.3)
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Requirement already satisfied: click<9,>=7.0 in /usr/local/lib/python3.8/dist-packages (from mlflow->pycaret[full]) (7.1.2)
Requirement already satisfied: sqlparse<1,>=0.4.0 in /usr/local/lib/python3.8/dist-packages (from mlflow->pycaret[full]) (0.4.3)
Requirement already satisfied: pytz<2023 in /usr/local/lib/python3.8/dist-packages (from mlflow->pycaret[full]) (2022.7.1)
Requirement already satisfied: pyarrow<11,>=4.0.0 in /usr/local/lib/python3.8/dist-packages (from mlflow->pycaret[full]) (9.0.0)
```

```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
```

Importando arquivo da pasta do Google Drive

```
from google.colab import drive
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

```
Dados = pd.read_csv('/content/drive/MyDrive/[Lighthouse] Desafio Cientista de Dados/desafio_manutencao_preditiva_treino.csv')
```

```
Dados
```

	udi	product_id	type	air_temperature_k	process_temperature_k	rotational_speed_rpm
0	1	M14860	M	298.1	308.6	1551
1	2	L47181	L	298.2	308.7	1408
2	5	L47184	L	298.2	308.7	1408
3	6	M14865	M	298.1	308.6	1425
4	7	L47186	L	298.1	308.6	1558
...
6662	9995	L57174	L	298.8	308.3	1634
6663	9996	M24855	M	298.8	308.4	1604
6664	9997	H39410	H	298.9	308.4	1632
6665	9999	H39412	H	299.0	308.7	1408

Pequena análise exploratória dos dados

6667 rows x 7 columns

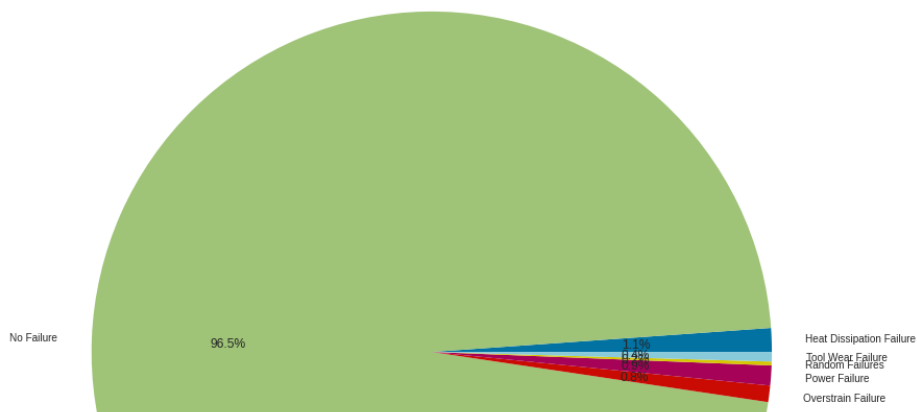
Dados.dtypes

```
udi              int64
product_id       object
type             object
air_temperature_k float64
process_temperature_k float64
rotational_speed_rpm int64
torque_nm        float64
tool_wear_min     int64
failure_type      object
dtype: object
```

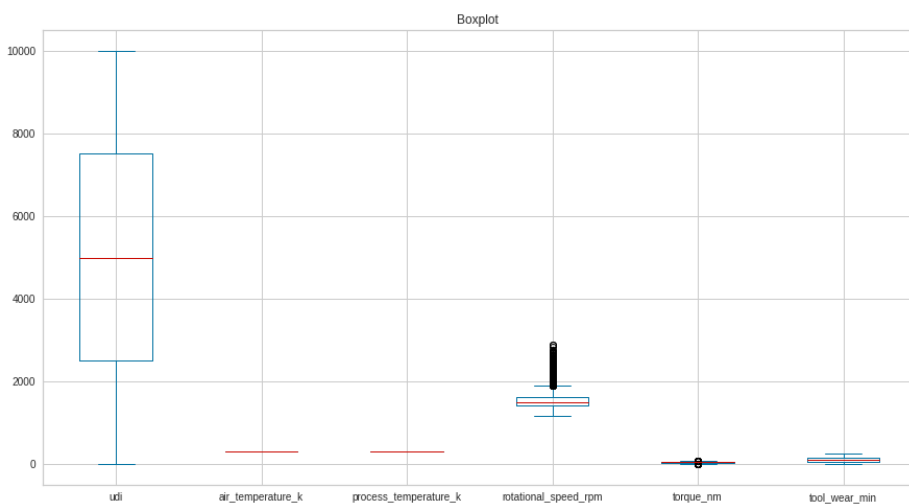
Dados.describe(include='all').T

	count	unique	top	freq	mean	std	min	25%
udi	6667.0	NaN	NaN	NaN	4994.589921	2896.125718	1.0	2496.5
product_id	6667	6667	M14860	1	NaN	NaN	NaN	NaN
type	6667	3	L	4022	NaN	NaN	NaN	NaN
air_temperature_k	6667.0	NaN	NaN	NaN	299.992515	1.99471	295.3	298.3
process_temperature_k	6667.0	NaN	NaN	NaN	309.99262	1.488101	305.7	308.8
rotational_speed_rpm	6667.0	NaN	NaN	NaN	1537.419529	177.182908	1168.0	1422.5
torque_nm	6667.0	NaN	NaN	NaN	40.058512	9.950804	3.8	33.2
tool_wear_min	6667.0	NaN	NaN	NaN	108.098095	63.359915	0.0	54.0
failure_type	6667	6	No Failure	6435	NaN	NaN	NaN	NaN

```
labels = Dados['failure_type'].astype('category').cat.categories.tolist()
counts = Dados['failure_type'].value_counts()
sizes = [counts[machine_name] for machine_name in labels]
plt.figure(figsize=(15,15))
plt.pie(sizes, labels=labels, autopct='%1.1f%%',shadow=False)
plt.title("Failure Type", fontsize=14)
plt.show()
```

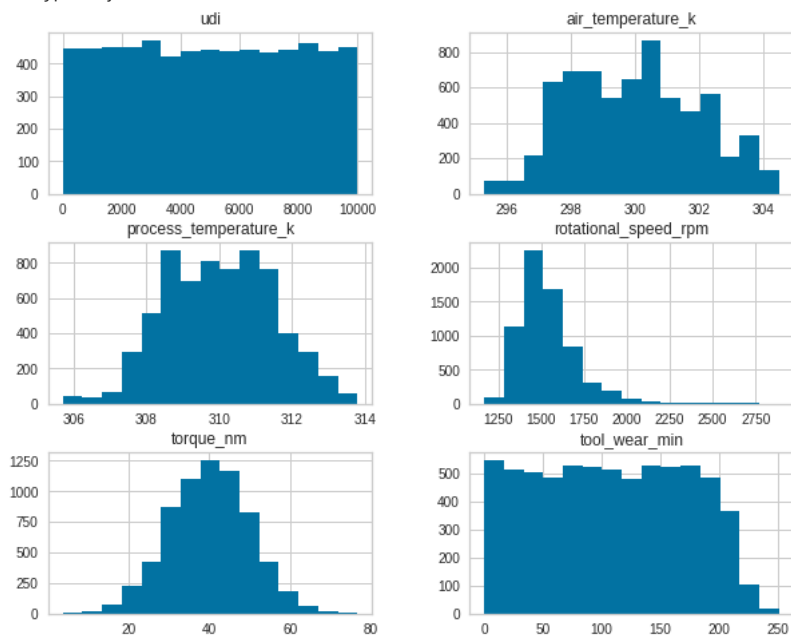


```
Dados.plot(kind='box', figsize=(15, 8))
plt.title('Boxplot ')
plt.show()
```



```
Dados.hist(bins=15,figsize=(10, 8))
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f0f2ff415b0>,
<matplotlib.axes._subplots.AxesSubplot object at 0x7f0f34045760>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x7f0f34535eb0>,
<matplotlib.axes._subplots.AxesSubplot object at 0x7f0f34534610>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x7f0f348c6d30>,
<matplotlib.axes._subplots.AxesSubplot object at 0x7f0f2fe963d0>]],
dtype=object)
```



Transformando a coluna de tipo de falha em Dummies para conseguir trabalhar melhor com o Dataset

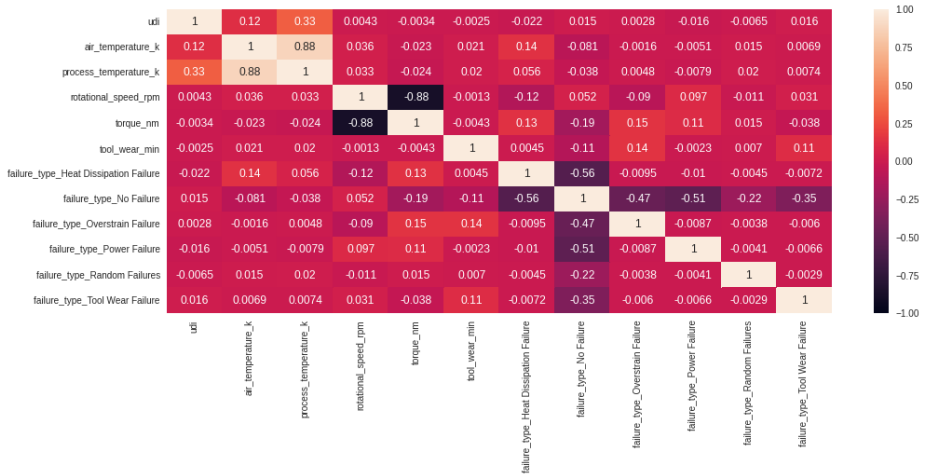
Dados = pd.get_dummies(Dados, columns = ['failure_type'])
Dados

	udi	product_id	type	air_temperature_k	process_temperature_k	rotational_speed_rpm
0	1	M14860	M	298.1	308.6	1551
1	2	L47181	L	298.2	308.7	1408
2	5	L47184	L	298.2	308.7	1408
3	6	M14865	M	298.1	308.6	1425
4	7	L47186	L	298.1	308.6	1558
...
6662	9995	L57174	L	298.8	308.3	1634
6663	9996	M24855	M	298.8	308.4	1604
6664	9997	H39410	H	298.9	308.4	1632
6665	9999	H39412	H	299.0	308.7	1408
6666	10000	M24859	M	299.0	308.7	1500

6667 rows x 14 columns

Tabela de Correlações

plt.figure(figsize=(16, 6))
sns.heatmap(Dados.corr(), vmin=-1, vmax=1, annot=True);



Retirando colunas que não parecem ser relevantes em comparação com os demais ou foram transformadas em Dummies.

Dados.drop(['udi', 'product_id', 'type', 'failure_type_No Failure'], axis=1, inplace=True)

Dados

	air_temperature_k	process_temperature_k	rotational_speed_rpm	torque_nm	tool_wear_r
0	298.1	308.6	1551	42.8	
1	298.2	308.7	1408	46.3	
2	298.2	308.7	1408	40.0	

Dividindo os dados, criando um dataset para cada tipo de falha:

```
DadosTWF = Dados
DadosTWF = DadosTWF.drop(['failure_type_Overstrain Failure', 'failure_type_Power Failure', 'failure_type_Random Failures', 'failure_type_Heat Dissipation Failure'], axis=1)
DadosTWF
```

	air_temperature_k	process_temperature_k	rotational_speed_rpm	torque_nm	tool_wear_r
0	298.1	308.6	1551	42.8	
1	298.2	308.7	1408	46.3	
2	298.2	308.7	1408	40.0	
3	298.1	308.6	1425	41.9	
4	298.1	308.6	1558	42.4	
...
6662	298.8	308.3	1634	27.9	
6663	298.8	308.4	1604	29.5	
6664	298.9	308.4	1632	31.8	
6665	299.0	308.7	1408	48.5	
6666	299.0	308.7	1500	40.2	

6667 rows × 6 columns

```
DadosHDF = Dados
DadosHDF = DadosHDF.drop(['failure_type_Overstrain Failure', 'failure_type_Random Failures', 'failure_type_Tool Wear Failure', 'failure_type_Power Failure'], axis=1)
DadosHDF
```

	air_temperature_k	process_temperature_k	rotational_speed_rpm	torque_nm	tool_wear_r
0	298.1	308.6	1551	42.8	
1	298.2	308.7	1408	46.3	
2	298.2	308.7	1408	40.0	
3	298.1	308.6	1425	41.9	
4	298.1	308.6	1558	42.4	
...
6662	298.8	308.3	1634	27.9	
6663	298.8	308.4	1604	29.5	
6664	298.9	308.4	1632	31.8	
6665	299.0	308.7	1408	48.5	
6666	299.0	308.7	1500	40.2	

```
DadosPWF = Dados
DadosPWF = DadosPWF.drop(['failure_type_Overstrain Failure', 'failure_type_Heat Dissipation Failure', 'failure_type_Random Failures', 'failure_type_Tool Wear Failure'], axis=1)
DadosPWF
```

	air_temperature_k	process_temperature_k	rotational_speed_rpm	torque_nm	tool_wear_r
0	298.1	308.6	1551	42.8	
1	298.2	308.7	1408	46.3	
2	298.2	308.7	1408	40.0	
3	298.1	308.6	1425	41.9	
4	298.1	308.6	1558	42.4	
...
6662	298.8	308.3	1634	27.9	
6663	298.8	308.4	1604	29.5	
6664	298.9	308.4	1632	31.8	

DadosOSF = Dados
DadosOSF = DadosOSF.drop(['failure_type_Power Failure','failure_type_Heat Dissipation Failure', 'failure_type_Random Failures', 'failure_type_Tool Wear Failure'], axis=1)
DadosOSF

	air_temperature_k	process_temperature_k	rotational_speed_rpm	torque_nm	tool_wear_r
0	298.1	308.6	1551	42.8	
1	298.2	308.7	1408	46.3	
2	298.2	308.7	1408	40.0	
3	298.1	308.6	1425	41.9	
4	298.1	308.6	1558	42.4	
...
6662	298.8	308.3	1634	27.9	
6663	298.8	308.4	1604	29.5	
6664	298.9	308.4	1632	31.8	
6665	299.0	308.7	1408	48.5	
6666	299.0	308.7	1500	40.2	

6667 rows × 6 columns

DadosRNF = Dados
DadosRNF = DadosRNF.drop(['failure_type_Power Failure','failure_type_Heat Dissipation Failure','failure_type_Overstrain Failure', 'failure_type_Tool Wear Failure'], axis=1)
DadosRNF

	air_temperature_k	process_temperature_k	rotational_speed_rpm	torque_nm	tool_wear_r
0	298.1	308.6	1551	42.8	
1	298.2	308.7	1408	46.3	
2	298.2	308.7	1408	40.0	
3	298.1	308.6	1425	41.9	
4	298.1	308.6	1558	42.4	
...
6662	298.8	308.3	1634	27.9	
6663	298.8	308.4	1604	29.5	
6664	298.9	308.4	1632	31.8	
6665	299.0	308.7	1408	48.5	
6666	299.0	308.7	1500	40.2	

6667 rows × 6 columns

Por vezes é necessário voltar para a primeira célula e reinstalar o pycaret #

from pycaret.classification import *

Selecionando, Criando e Salvando o Modelo para RNF

RNF = setup(data = DadosRNF, target = 'failure_type_Random Failures')
compare_models()

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
lr	Logistic Regression	0.9983	0.3058	0.0	0.0	0.0	NaN	0.0000	0.047
knn	K Neighbors Classifier	0.9983	0.3975	0.0	0.0	0.0	NaN	0.0000	0.036
nb	Naive Bayes	0.9983	0.3647	0.0	0.0	0.0	NaN	0.0000	0.017
svm	SVM - Linear Kernel	0.9983	0.0000	0.0	0.0	0.0	NaN	0.0000	0.026
ridge	Ridge Classifier	0.9983	0.0000	0.0	0.0	0.0	NaN	0.0000	0.016
rf	Random Forest Classifier	0.9983	0.4714	0.0	0.0	0.0	NaN	0.0000	0.566
qda	Quadratic Discriminant Analysis	0.9983	0.2023	0.0	0.0	0.0	NaN	0.0000	0.030
lda	Linear Discriminant Analysis	0.9983	0.3833	0.0	0.0	0.0	NaN	0.0000	0.020
et	Extra Trees Classifier	0.9983	0.4726	0.0	0.0	0.0	NaN	0.0000	0.245
xgboost	Extreme Gradient Boosting	0.9983	0.4935	0.0	0.0	0.0	NaN	0.0000	0.161
catboost	CatBoost Classifier	0.9983	0.4389	0.0	0.0	0.0	NaN	0.0000	4.802
dummy	Dummy Classifier	0.9983	0.4000	0.0	0.0	0.0	NaN	0.0000	0.014
ada	Ada Boost Classifier	0.9981	0.3305	0.0	0.0	0.0	NaN	-0.0002	0.385
lightgbm	Light Gradient Boosting Machine	0.9979	0.4592	0.0	0.0	0.0	NaN	-0.0002	0.187
gbc	Gradient Boosting Classifier	0.9976	0.5183	0.0	0.0	0.0	NaN	-0.0004	0.604
dt	Decision Tree Classifier	0.9968	0.3994	0.0	0.0	0.0	NaN	-0.0012	0.020

INFO:logs:create_model_container: 16
INFO:logs:master_model_container: 16
INFO:logs:display_container: 2
INFO:logs:LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True, intercept_scaling=1, l1_ratio=None, max_iter=1000, multi_class='auto', n_jobs=None, penalty='l2', random_state=8168, solver='lbfgs', tol=0.0001, verbose=0, warm_start=False)

RNF_model = create_model('lr')

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.9979	0.4099	0.0	0.0	0.0	0.0	0.0
1	0.9979	0.4399	0.0	0.0	0.0	0.0	0.0
2	0.9979	0.2425	0.0	0.0	0.0	0.0	0.0
3	0.9979	0.0472	0.0	0.0	0.0	0.0	0.0
4	0.9979	0.3820	0.0	0.0	0.0	0.0	0.0
5	0.9979	0.4592	0.0	0.0	0.0	0.0	0.0
6	1.0000	0.0000	0.0	0.0	0.0	NaN	0.0
7	1.0000	0.0000	0.0	0.0	0.0	NaN	0.0
8	0.9979	0.8022	0.0	0.0	0.0	0.0	0.0
9	0.9979	0.2753	0.0	0.0	0.0	0.0	0.0
Mean	0.9983	0.3058	0.0	0.0	0.0	NaN	0.0
Std	0.0009	0.2374	0.0	0.0	0.0	NaN	0.0

INFO:logs:create_model_container: 17
INFO:logs:master_model_container: 17
INFO:logs:display_container: 3
INFO:logs:LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True, intercept_scaling=1, l1_ratio=None, max_iter=1000, multi_class='auto', n_jobs=None, penalty='l2', random_state=8168, solver='lbfgs', tol=0.0001, verbose=0, warm_start=False)
INFO:logs:create_model() succesfully completed.....

modelo_final_RNF = finalize_model(RNF_model)

INFO:logs:Initializing finalize_model()
INFO:logs:finalize_model(estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True, intercept_scaling=1, l1_ratio=None, max_iter=1000, multi_class='auto', n_jobs=None, penalty='l2', random_state=8168, solver='lbfgs', tol=0.0001, verbose=0, warm_start=False), fit_kwargs=None, groups=None, model_only=True, display=None, experiment_custom_tags=None, return_train_score=False)

```
INFO:logs:Finalizing LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, l1_ratio=None, max_iter=1000,
    multi_class='auto', n_jobs=None, penalty='l2',
    random_state=8168, solver='lbfgs', tol=0.0001, verbose=0,
    warm_start=False)
INFO:logs:Initializing create_model()
INFO:logs:create_model(estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, l1_ratio=None, max_iter=1000,
    multi_class='auto', n_jobs=None, penalty='l2',
    random_state=8168, solver='lbfgs', tol=0.0001, verbose=0,
    warm_start=False), fold=None, round=4, cross_validation=True, predict=True, fit_kwargs={}, groups=None, refit=True, verbose=False, system=False, metrics=None, exp
INFO:logs:Checking exceptions
INFO:logs:Importing libraries
INFO:logs:Copying training dataset
INFO:logs:Defining folds
INFO:logs:Declaring metric variables
INFO:logs:Importing untrained model
INFO:logs:Declaring custom model
INFO:logs:Logistic Regression Imported succesfully
INFO:logs:Starting cross validation
INFO:logs:Cross validating with StratifiedKFold(n_splits=10, random_state=None, shuffle=False), n_jobs=-1
INFO:logs:Calculating mean and std
INFO:logs:Creating metrics dataframe
INFO:logs:Finalizing model
INFO:logs:create_model_container: 17
INFO:logs:master_model_container: 17
INFO:logs:display_container: 4
INFO:logs:LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, l1_ratio=None, max_iter=1000,
    multi_class='auto', n_jobs=None, penalty='l2',
    random_state=8168, solver='lbfgs', tol=0.0001, verbose=0,
    warm_start=False)
INFO:logs:create_model() succesfully completed.....
INFO:logs:create_model_container: 17
INFO:logs:master_model_container: 17
INFO:logs:display_container: 3
INFO:logs:LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, l1_ratio=None, max_iter=1000,
    multi_class='auto', n_jobs=None, penalty='l2',
    random_state=8168, solver='lbfgs', tol=0.0001, verbose=0,
    warm_start=False)
INFO:logs:finalize_model() succesfully completed.....
```

save_model(modelo_final_RNF, 'modelo_RNF')

```
INFO:logs:Initializing save_model()
INFO:logs:save_model(model=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, l1_ratio=None, max_iter=1000,
    multi_class='auto', n_jobs=None, penalty='l2',
    random_state=8168, solver='lbfgs', tol=0.0001, verbose=0,
    warm_start=False), model_name=modelo_RNF, prep_pipe_=Pipeline(memory=None,
    steps=[('dtypes',
        DataTypes_Auto_infer(categorical_features=[],
            display_types=True, features_todrop=[],
            id_columns=[],
            ml_usecase='classification',
            numerical_features=[],
            target='failure_type_Random Failures',
            time_features=[])),
        ('imputer',
            Simple_Imputer(categorical_strategy='not_available',
                fill_value_categorical=None,
                fill_value_numeric...
            ('binn', 'passthrough'), ('rem_outliers', 'passthrough'),
            ('cluster_all', 'passthrough'),
            ('dummy', Dummify(target='failure_type_Random Failures')),
            ('fix_perfect',
                Remove_100(target='failure_type_Random Failures')),
            ('clean_names', Clean_Column_Names()),
            ('feature_select', 'passthrough'), ('fix_multi', 'passthrough'),
            ('dfs', 'passthrough'), ('pca', 'passthrough')),
        verbose=False), verbose=True, kwargs={})
INFO:logs:Adding model into prep_pipe
INFO:logs:modelo_RNF.pkl saved in current working directory
INFO:logs:Pipeline(memory=None,
    steps=[('dtypes',
        DataTypes_Auto_infer(categorical_features=[],
            display_types=True, features_todrop=[],
            id_columns=[],
            ml_usecase='classification',
            numerical_features=[],
            target='failure_type_Random Failures',
            time_features=[])),
        ('imputer',
            Simple_Imputer(categorical_strategy='not_available',
                fill_value_categorical=None,
                fill_value_numeric...
            ('feature_select', 'passthrough'), ('fix_multi', 'passthrough'),
            ('dfs', 'passthrough'), ('pca', 'passthrough'),
            ['trained_model',
                LogisticRegression(C=1.0, class_weight=None, dual=False,
                    fit_intercept=True, intercept_scaling=1,
                    l1_ratio=None, max_iter=1000,
```



```
OSF_model = create_model('lightgbm')
modelo_final_OSF = finalize_model(OSF_model)
save_model(modelo_final_OSF, 'modelo_OSF')
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.9936	0.9935	0.5000	0.6667	0.5714	0.5683	0.5742
1	0.9957	0.9978	0.5000	1.0000	0.6667	0.6648	0.7056
2	0.9979	0.9989	1.0000	0.8000	0.8889	0.8878	0.8935
3	0.9957	0.9973	0.7500	0.7500	0.7500	0.7478	0.7478
4	0.9893	0.9978	0.0000	0.0000	0.0000	-0.0034	-0.0043
5	0.9957	0.9968	0.7500	0.7500	0.7500	0.7478	0.7478
6	0.9936	0.9971	0.3333	0.5000	0.4000	0.3969	0.4052
7	0.9979	0.9993	1.0000	0.7500	0.8571	0.8561	0.8651
8	0.9893	0.9892	0.2500	0.3333	0.2857	0.2804	0.2834
9	0.9914	0.9973	0.5000	0.5000	0.5000	0.4957	0.4957
Mean	0.9940	0.9965	0.5583	0.6050	0.5670	0.5642	0.5714
Std	0.0030	0.0029	0.3052	0.2689	0.2641	0.2651	0.2680

n_estimators=100, n_jobs=-1, num_leaves=31, objective=None,

Selecionando, Criando e Salvando o Modelo para PWF

steps=11, types,

PWF = setup(data = DadosPWF, target = 'failure_type_Power Failure')
compare_models()

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
lr	Logistic Regression	0.9976	0.9991	0.865	0.8988	0.8711	0.8700	0.8754	0.081
xgboost	Extreme Gradient Boosting	0.9970	0.9935	0.835	0.8483	0.8350	0.8335	0.8369	0.256
dt	Decision Tree Classifier	0.9964	0.8941	0.790	0.8300	0.7957	0.7939	0.8010	0.033
lightgbm	Light Gradient Boosting Machine	0.9964	0.9809	0.735	0.8517	0.7802	0.7784	0.7849	0.179
ada	Ada Boost Classifier	0.9961	0.9869	0.720	0.8567	0.7615	0.7597	0.7729	0.187
et	Extra Trees Classifier	0.9961	0.9989	0.660	0.9167	0.7563	0.7545	0.7703	0.356
gbc	Gradient Boosting Classifier	0.9959	0.9508	0.745	0.8100	0.7635	0.7615	0.7684	0.411
rf	Random Forest Classifier	0.9957	0.9857	0.730	0.8250	0.7648	0.7626	0.7690	0.686
catboost	CatBoost Classifier	0.9957	0.9982	0.755	0.8217	0.7694	0.7673	0.7768	4.498
qda	Quadratic Discriminant Analysis	0.9953	0.9975	0.870	0.7179	0.7801	0.7777	0.7847	0.017
knn	K Neighbors Classifier	0.9923	0.7385	0.280	0.6750	0.3860	0.3833	0.4252	0.076
lda	Linear Discriminant Analysis	0.9921	0.9960	0.655	0.5683	0.6004	0.5965	0.6021	0.020
ridge	Ridge Classifier	0.9908	0.0000	0.000	0.0000	0.0000	0.0000	0.0000	0.024
dummy	Dummy Classifier	0.9908	0.5000	0.000	0.0000	0.0000	0.0000	0.0000	0.025
svm	SVM - Linear Kernel	0.9843	0.0000	0.095	0.2667	0.1305	0.1282	0.1492	0.041
nb	Naive Bayes	0.9820	0.9738	0.325	0.1998	0.2442	0.2359	0.2446	0.026

INFO:logs:create_model_container: 16
INFO:logs:master_model_container: 16
INFO:logs:display_container: 2
INFO:logs:LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True, intercept_scaling=1, l1_ratio=None, max_iter=1000, multi_class='auto', n_jobs=None, penalty='l2', random_state=None)
INFO:logs:Information about the model successfully saved to file: /home/.../model.pkl

PWF_model = create_model('lr')
modelo_final_PWF = finalize_model(PWF_model)
save_model(modelo_final_PWF, 'modelo_PWF')

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3	0.9936	0.9974	0.6000	0.7500	0.6667	0.6635	0.6677
4	0.9979	0.9991	0.8000	1.0000	0.8889	0.8878	0.8935
5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
6	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
7	0.9936	0.9968	0.5000	0.6667	0.5714	0.5683	0.5742
8	0.9979	1.0000	0.7500	1.0000	0.8571	0.8561	0.8651
9	0.9936	0.9978	1.0000	0.5714	0.7273	0.7243	0.7535
Mean	0.9976	0.9991	0.8650	0.8988	0.8711	0.8700	0.8754
Std	0.0028	0.0012	0.1817	0.1597	0.1536	0.1549	0.1506

ml_usecase='classification',

Selecionando, Criando e Salvando o Modelo para HDF

time_features=1]],

HDF = setup(data = DadosHDF, target = 'failure_type_Heat Dissipation Failure')
compare_models()

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
lightgbm	Light Gradient Boosting Machine	0.9970	0.9826	0.8000	0.9548	0.8637	0.8623	0.8691	0.090
ada	Ada Boost Classifier	0.9964	0.9962	0.7833	0.9148	0.8339	0.8321	0.8397	0.369
xgboost	Extreme Gradient Boosting	0.9964	0.9973	0.7600	0.9217	0.8233	0.8215	0.8303	0.147
catboost	CatBoost Classifier	0.9961	0.9979	0.7200	0.9500	0.7959	0.7942	0.8119	4.745
gbc	Gradient Boosting Classifier	0.9959	0.9946	0.7833	0.8883	0.8170	0.8150	0.8244	0.623
dt	Decision Tree Classifier	0.9942	0.8604	0.7233	0.8100	0.7516	0.7487	0.7563	0.019
rf	Random Forest Classifier	0.9936	0.9875	0.5600	0.8821	0.6698	0.6668	0.6917	0.547
qda	Quadratic Discriminant Analysis	0.9934	0.9965	0.6267	0.7558	0.6734	0.6702	0.6790	0.029
lr	Logistic Regression	0.9916	0.9949	0.4300	0.7350	0.5226	0.5190	0.5464	0.046
et	Extra Trees Classifier	0.9912	0.9950	0.2900	0.8333	0.4222	0.4193	0.4826	0.250
knn	K Neighbors Classifier	0.9882	0.7095	0.0000	0.0000	0.0000	0.0000	0.0000	0.042
svm	SVM - Linear Kernel	0.9882	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.027
ridge	Ridge Classifier	0.9882	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.015
lda	Linear Discriminant Analysis	0.9882	0.9854	0.0200	0.1000	0.0333	0.0327	0.0440	0.023
dummy	Dummy Classifier	0.9882	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.015
nb	Naive Bayes	0.9831	0.9888	0.7333	0.4143	0.5217	0.5141	0.5395	0.018

INFO:logs:create_model_container: 16
INFO:logs:master_model_container: 16
INFO:logs:display_container: 2
INFO:logs:LGBMClassifier(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0, importance_type='split', learning_rate=0.1, max_depth=-1, min_child_samples=20, min_child_weight=0.001, min_split_gain=0.0, n_estimators=100, n_jobs=-1, num_leaves=31, objective=None, target=failure_type_Power Failure ,

HDF_model = create_model('lightgbm')
modelo_final_HDF = finalize_model(HDF_model)
save_model(modelo_final_PWF, 'modelo_HDF')

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.9979	1.0000	0.8000	1.0000	0.8889	0.8878	0.8935
1	0.9957	0.9996	0.6667	1.0000	0.8000	0.7979	0.8147
2	0.9957	0.9986	0.8333	0.8333	0.8333	0.8312	0.8312
3	0.9979	0.9996	0.8333	1.0000	0.9091	0.9080	0.9119
4	0.9979	0.9946	0.8333	1.0000	0.9091	0.9080	0.9119
5	0.9936	0.8344	0.8333	0.7143	0.7692	0.7660	0.7683
6	0.9957	0.9996	0.6000	1.0000	0.7500	0.7480	0.7729
7	0.9979	1.0000	0.8000	1.0000	0.8889	0.8878	0.8935
8	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
9	0.9979	1.0000	0.8000	1.0000	0.8889	0.8878	0.8935
Mean	0.9970	0.9826	0.8000	0.9548	0.8637	0.8623	0.8691
Std	0.0017	0.0494	0.1011	0.0943	0.0717	0.0725	0.0681

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.9957	0.9785	0.0	0.0	0.0	0.0000	0.0000
1	0.9957	0.9645	0.0	0.0	0.0	0.0000	0.0000
2	0.9936	0.9713	0.0	0.0	0.0	0.0000	0.0000
3	0.9936	0.9741	0.0	0.0	0.0	0.0000	0.0000
4	0.9936	0.9835	0.0	0.0	0.0	0.0000	0.0000
5	0.9936	0.9770	0.0	0.0	0.0	0.0000	0.0000
6	0.9957	0.9580	0.0	0.0	0.0	0.0000	0.0000
7	0.9957	0.9881	0.0	0.0	0.0	0.0000	0.0000
8	0.9957	0.9709	0.0	0.0	0.0	0.0000	0.0000
9	0.9936	0.9580	0.0	0.0	0.0	-0.0029	-0.0030
Mean	0.9946	0.9724	0.0	0.0	0.0	-0.0003	-0.0003
Std	0.0011	0.0096	0.0	0.0	0.0	0.0009	0.0009

ml_usecase='classification',

Finalizada Etapa dos Modelos e testes, agora é hora de utilizar os modelos e salvar as predições conforme exigido.

Simple Imputer(categorical_strategy='not_available')

Abrindo a planilha de Teste

['kinc' 'backthrough') ('rom_outliers' 'backthrough')

(testing, testing(target = feature_type_100, test = feature_100))

Teste = pd.read_csv('/content/drive/MyDrive/([Lighthouse] Desafio Cientista de Dados/desafio_manutencao_preditiva_teste.csv')

Teste

	udi	product_id	type	air_temperature_k	process_temperature_k	rotational_speed_rpm
0	446	L47625	L	297.5	308.6	1793
1	7076	L54255	L	300.7	310.5	1536
2	1191	L48370	L	297.2	308.4	1460
3	2618	L49797	L	299.4	309.1	1670
4	5067	L52246	L	304.1	313.1	1550
...
3328	5554	L52733	L	302.5	311.9	1306
3329	6961	L54140	L	300.7	311.0	1413
3330	6914	L54093	L	300.8	311.2	1481
3331	5510	L52689	L	302.8	312.2	1509
3332	3066	M17925	M	300.1	309.2	1687

3333 rows × 8 columns

warm_start=False)]].

Aplicando os modelos de cada uma das falhas que criamos anteriormente

Transformation Pipeline and Model Successfullv Saved

df = Teste

modelo = load_model('modelo_HDF')

dff['predictedValues_HDF']=modelo.predict(dff[['air_temperature_k','process_temperature_k','rotational_speed_rpm','torque_nm','tool_wear_min']])

print(dff['predictedValues_HDF'])

INFO:logs:Initializing load_model()
INFO:logs:load_model(model_name=modelo_HDF, platform=None, authentication=None, verbose=True)
Transformation Pipeline and Model Successfully Loaded
0 0
1 0
2 0
3 0
4 0
..
3328 0
3329 0
3330 0
3331 0
3332 0
Name: predictedValues_HDF, Length: 3333, dtype: uint8

df

	udi	product_id	type	air_temperature_k	process_temperature_k	rotational_speed_rpm
0	446	L47625	L	297.5	308.6	1793

```
df2 = df
modelo = load_model('modelo_OSF')

df2['predictedValues_OSF']=modelo.predict(df[['air_temperature_k','process_temperature_k','rotational_speed_rpm','torque_nm','tool_wear_min']])
print(df2['predictedValues_OSF'])
```

```
INFO:logs:Initializing load_model()
INFO:logs:load_model(model_name=modelo_OSF, platform=None, authentication=None, verbose=True)
Transformation Pipeline and Model Successfully Loaded
0    0
1    0
2    0
3    0
4    0
..
3328  0
3329  0
3330  0
3331  0
3332  0
Name: predictedValues_OSF, Length: 3333, dtype: uint8
```

df2

	udi	product_id	type	air_temperature_k	process_temperature_k	rotational_speed_rpm
0	446	L47625	L	297.5	308.6	1793
1	7076	L54255	L	300.7	310.5	1536
2	1191	L48370	L	297.2	308.4	1460
3	2618	L49797	L	299.4	309.1	1670
4	5067	L52246	L	304.1	313.1	1550
...
3328	5554	L52733	L	302.5	311.9	1306
3329	6961	L54140	L	300.7	311.0	1413
3330	6914	L54093	L	300.8	311.2	1481
3331	5510	L52689	L	302.8	312.2	1509
3332	3066	M17925	M	300.1	309.2	1687

3333 rows x 10 columns

```
df3 = df2
modelo = load_model('modelo_PWF')

df3['predictedValues_PWF']=modelo.predict(df[['air_temperature_k','process_temperature_k','rotational_speed_rpm','torque_nm','tool_wear_min']])
print(df3['predictedValues_PWF'])
```

```
INFO:logs:Initializing load_model()
INFO:logs:load_model(model_name=modelo_PWF, platform=None, authentication=None, verbose=True)
Transformation Pipeline and Model Successfully Loaded
0    0
1    0
2    0
3    0
4    0
..
3328  0
3329  0
3330  0
3331  0
3332  0
Name: predictedValues_PWF, Length: 3333, dtype: uint8
```

```
df4 = df3
modelo = load_model('modelo_RNF')
```

```
df4['predictedValues_RNF']=modelo.predict(df[['air_temperature_k','process_temperature_k','rotational_speed_rpm','torque_nm','tool_wear_min']])
print(df4['predictedValues_RNF'])
```

```
INFO:logs:Initializing load_model()
INFO:logs:load_model(model_name=modelo_RNF, platform=None, authentication=None, verbose=True)
Transformation Pipeline and Model Successfully Loaded
0    0
1    0
2    0
```

```
3 0
4 0
..
3328 0
3329 0
3330 0
3331 0
3332 0
Name: predictedValues_RNF, Length: 3333, dtype: uint8
```

```
df5 = df4
modelo = load_model('modelo_TWF')
```

```
df5['predictedValues_TWF']=modelo.predict(df[['air_temperature_k','process_temperature_k','rotational_speed_rpm','torque_nm','tool_wear_min']])
print(df5['predictedValues_TWF'])
```

```
INFO:logs:Initializing load_model()
INFO:logs:load_model(model_name=modelo_TWF, platform=None, authentication=None, verbose=True)
Transformation Pipeline and Model Successfully Loaded
0 0
1 0
2 0
3 0
4 0
..
3328 0
3329 0
3330 0
3331 0
3332 0
Name: predictedValues_TWF, Length: 3333, dtype: uint8
```

df5

	udi	product_id	type	air_temperature_k	process_temperature_k	rotational_speed_rpm
0	446	L47625	L	297.5	308.6	1793
1	7076	L54255	L	300.7	310.5	1536
2	1191	L48370	L	297.2	308.4	1460
3	2618	L49797	L	299.4	309.1	1670
4	5067	L52246	L	304.1	313.1	1550
...
3328	5554	L52733	L	302.5	311.9	1306
3329	6961	L54140	L	300.7	311.0	1413
3330	6914	L54093	L	300.8	311.2	1481
3331	5510	L52689	L	302.8	312.2	1509
3332	3066	M17925	M	300.1	309.2	1687

3333 rows × 7 columns

Exportando para CSV, será finalizado por lá daí, transformando os 1 das colunas de predição para o seu devido nome de erro e unificando as colunas

```
from google.colab import files
df5.to_csv('predicted raw.csv', encoding = 'utf-8-sig')
files.download('predicted raw.csv')
```

