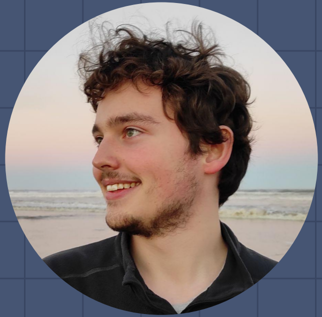
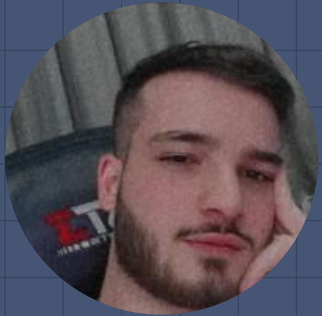
Treinamento e validação de modelos preditivos com AM

GRUPO



Rafael Petry
00314280



Lucas Melo
00315747

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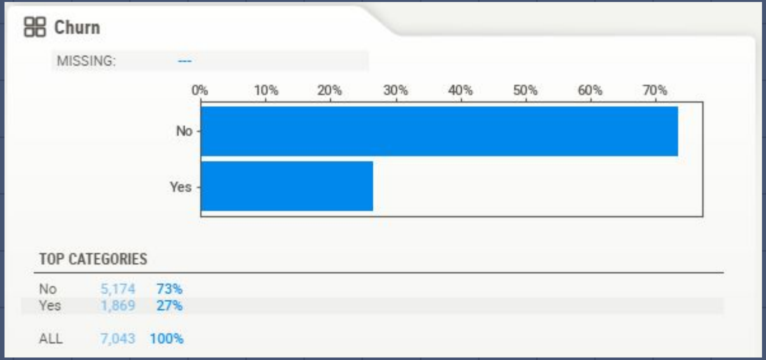
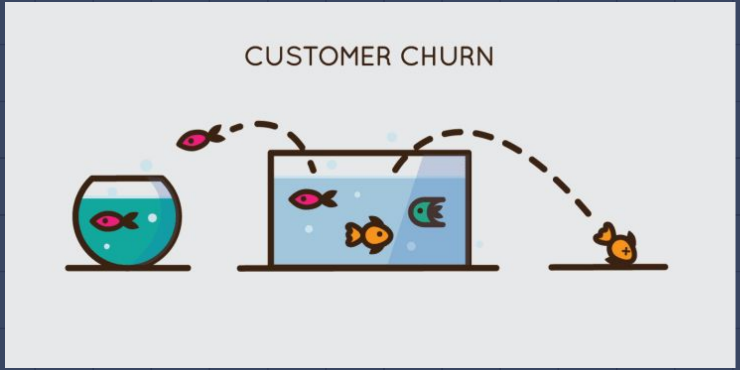
DATASET

Optamos pelo dataset
"Telco Customer Churn" da IBM que contém dados sobre os clientes e serviços contratados





Coluna	Intervalo
gender	[Male, Female]
SeniorCitizen	[0, 1]
Partner	[Yes, No]
Dependents	[Yes, No]
Tenure	[0, ..., 72]
PhotoService	[Yes, No]
MultipleLines	[Yes, No, No service]
InternetService	[DSL, Fiber, No service]
OnlineSecurity	[Yes, No, No service]
OnlineBackup	[Yes, No, No service]

Coluna	Intervalo
DeviceProtection	[Yes, No, No service]
TechSupport	[Yes, No, No service]
StreamingTV	[Yes, No, No service]
StreamingMovies	[Yes, No, No service]
Contract	[Monthly, One Year, Two Years]
PaperlessBilling	[Yes, No]
PaymentMethod	[E-check, Mail-Check, Transfer, Credit Card]
MonthlyCharges	[18.30, ..., 119.00]
*TotalCharges	[18.80, 8684.80]
Churn	[Yes, No]

Qual a probabilidade de um cliente cancelar o serviço?

ATRIBUTOS

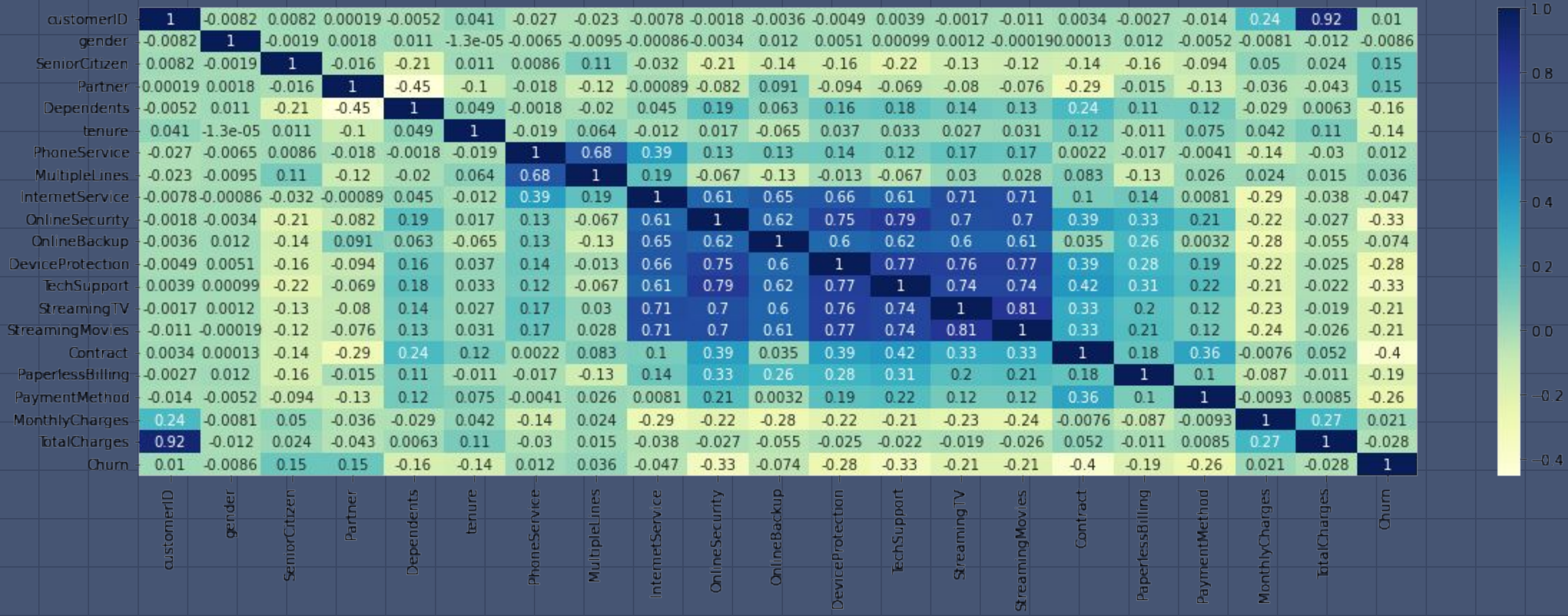
Irrelevantes / Removidos

- customerID - Somente ID do cliente não é importante.
- StreamingTV-Baseado na análise de correlação.

Principais

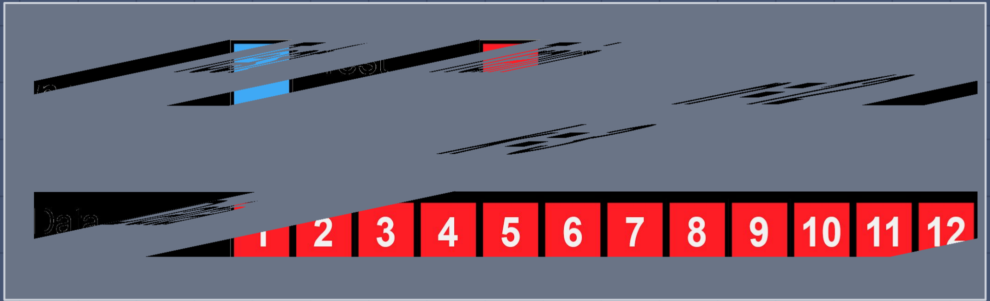
- TotalCharges - Total pago no quarter
- MonthlyCharges - Mensalidade total paga
- Tenure - Total de meses que a pessoa é cliente
- Churn (target - se cliente cancelou)

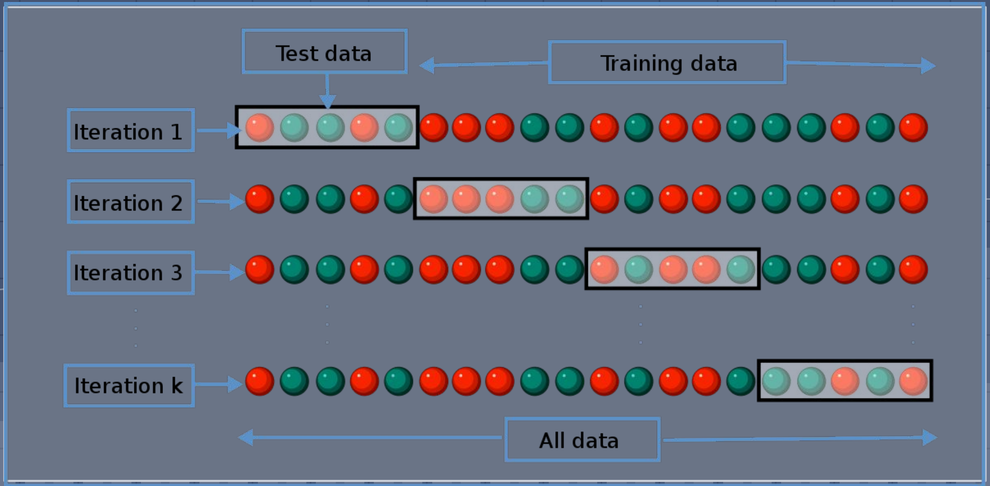
Correlação


customerID 1 -0.0082 0.0082 0.00019 -0.0052 0.041 -0.027 -0.023 -0.0078 -0.0018 -0.0036 -0.0049 0.0039 -0.0017 -0.011 0.0034 -0.0027 -0.014 0.24 0.92 0.01
gender -0.0082 1 -0.0019 0.0018 0.011 -1.3e-05 -0.0065 -0.0095 -0.00086 -0.0034 0.012 0.0051 0.00099 0.0012 -0.00019 0.00013 0.012 -0.0052 -0.0081 -0.012 -0.0086
SeniorCitizen 0.0082 -0.0019 1 -0.016 -0.21 0.011 0.0086 0.11 -0.032 -0.21 -0.14 -0.16 -0.22 -0.13 -0.12 -0.14 -0.16 -0.094 0.05 0.024 0.15
Partner 0.00019 0.0018 -0.016 1 -0.45 -0.1 -0.018 -0.12 -0.00089 -0.082 0.091 -0.094 -0.069 -0.08 -0.076 -0.29 -0.015 -0.13 -0.036 -0.043 0.15
Dependents -0.0052 0.011 -0.21 -0.45 1 0.049 -0.0018 -0.02 0.045 0.19 0.063 0.16 0.18 0.14 0.13 0.24 0.11 0.12 -0.029 0.0063 -0.16
tenure 0.041 -1.3e-05 0.011 -0.1 0.049 1 -0.019 0.064 -0.012 0.017 -0.065 0.037 0.033 0.027 0.031 0.12 -0.011 0.075 0.042 0.11 -0.14
PhoneService -0.027 -0.0065 0.0086 -0.018 -0.0018 -0.019 1 0.68 0.39 0.13 0.13 0.14 0.12 0.17 0.17 0.0022 -0.017 -0.0041 -0.14 -0.03 0.012
MultipleLines -0.023 -0.0095 0.11 -0.12 -0.02 0.064 0.68 1 0.19 -0.067 -0.13 -0.013 -0.067 0.03 0.028 0.083 -0.13 0.026 0.024 0.015 0.036
InternetService -0.0078 -0.00086 -0.032 -0.00089 0.045 -0.012 0.39 0.19 1 0.61 0.65 0.66 0.61 0.71 0.71 0.1 0.14 0.0081 -0.29 -0.038 -0.047
OnlineSecurity -0.0018 -0.0034 -0.21 -0.082 0.19 0.017 0.13 -0.067 0.61 1 0.62 0.75 0.79 0.7 0.7 0.39 0.33 0.21 -0.22 -0.027 -0.33
OnlineBackup -0.0036 0.012 -0.14 0.091 0.063 -0.065 0.13 -0.13 0.65 0.62 1 0.6 0.62 0.6 0.61 0.035 0.26 0.0032 -0.28 -0.055 -0.074
DeviceProtection -0.0049 0.0051 -0.16 -0.094 0.16 0.037 0.14 -0.013 0.66 0.75 0.6 1 0.77 0.76 0.77 0.39 0.28 0.19 -0.22 -0.025 -0.28
TechSupport 0.0039 0.00099 -0.22 -0.069 0.18 0.033 0.12 -0.067 0.61 0.79 0.62 0.77 1 0.74 0.74 0.42 0.31 0.22 -0.21 -0.022 -0.33
StreamingTV -0.0017 0.0012 -0.13 -0.08 0.14 0.027 0.17 0.03 0.71 0.7 0.6 0.76 0.74 1 0.81 0.33 0.2 0.12 -0.23 -0.019 -0.21
StreamingMovies -0.011 -0.00019 -0.12 -0.076 0.13 0.031 0.17 0.028 0.71 0.7 0.61 0.77 0.74 0.81 1 0.33 0.21 0.12 -0.24 -0.026 -0.21
Contract 0.0034 0.00013 -0.14 -0.29 0.24 0.12 0.0022 0.083 0.1 0.39 0.035 0.39 0.42 0.33 0.33 1 0.18 0.36 -0.0076 0.052 -0.4
PaperlessBilling -0.0027 0.012 -0.16 -0.015 0.11 -0.011 -0.017 -0.13 0.14 0.33 0.26 0.28 0.31 0.2 0.21 0.18 1 0.1 -0.087 -0.011 -0.19
PaymentMethod -0.014 -0.0052 -0.094 -0.13 0.12 0.075 -0.0041 0.026 0.0081 0.21 0.0032 0.19 0.22 0.12 0.12 0.36 0.1 1 -0.0093 0.0085 -0.26
MonthlyCharges 0.24 -0.0081 0.05 -0.036 -0.029 0.042 -0.14 0.024 -0.29 -0.22 -0.28 -0.22 -0.21 -0.23 -0.24 -0.0076 -0.087 -0.0093 1 0.27 0.021
TotalCharges 0.92 -0.012 0.024 -0.043 0.0063 0.11 -0.03 0.015 -0.038 -0.027 -0.055 -0.025 -0.022 -0.019 -0.026 0.052 -0.011 0.0085 0.27 1 -0.028
Churn 0.01 -0.0086 0.15 0.15 -0.16 -0.14 0.012 0.036 -0.047 -0.33 -0.074 -0.28 -0.33 -0.21 -0.21 -0.4 -0.19 -0.26 0.021 -0.028 1
customerID gender SeniorCitizen Partner Dependents tenure PhoneService MultipleLines InternetService OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV StreamingMovies Contract PaperlessBilling PaymentMethod MonthlyCharges TotalCharges Churn
1.0 0.8 0.6 0.4 0.2 0.0 −0.2 −0.4

K-fold cross validation

1. Divida aleatóriamente os dados em *k* subconjuntos (folds)
2. Use a parte dos dados como treino
3. Use o fold j para teste
4. Repita o processo *k* vezes





K-fold cross validation

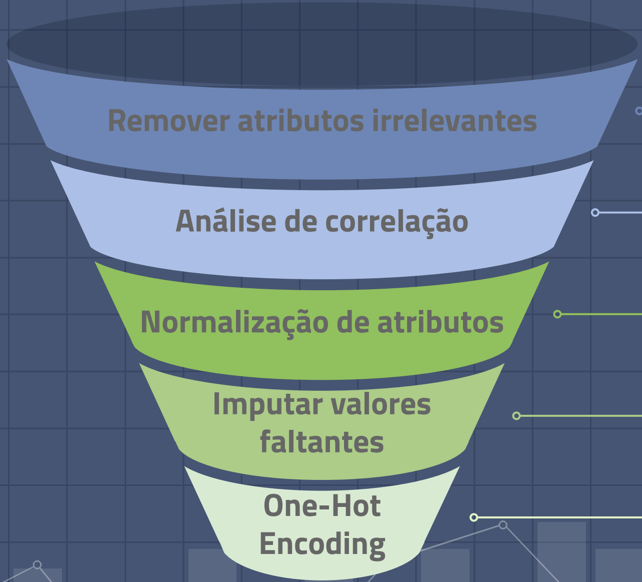
```
def random_k_folds(instance_list: List[Instance], k: int, merge_remainders=True):
    instances = instance_list.copy()
    random.Random(0).shuffle(instances)
    max_fold_size = len(instances) // k
    k_folds = [instances[i * max_fold_size:(i + 1) * max_fold_size] for i in range(k)
    ]
    remainders = instances[k * max_fold_size:]
    return remainders_merge_policy(k_folds, remainders) if merge_remainders else (
    k_folds, remainders)
```

```
def stratified_k_folds(instance_list: List[Instance], k: int, merge_remainders=True):
    instances = instance_list.copy()
    labels = {i.label() for i in instances}
    labeled_instances = {l: [i for i in instances if i.label() == l] for l in labels}
    label_folds = [random_k_folds(labeled_instances[l], k, merge_remainders=False)
    for l in labels]
    labeled_k_folds = [[e for l in f for e in l] for f, r in label_folds]
    k_folds = [[e for l in labeled_k_folds for e in l[i * len(l) // k:(i + 1) * len(l
    ) // k]] for i in range(k)]
    k_folds = [sorted(k, key=operator.attrgetter('_instance_data')) for k in k_folds]
    remainders = [e for f, r in label_folds for e in r]
    return remainders_merge_policy(k_folds, remainders) if merge_remainders else (
    k_folds, remainders)
```

```
class Instance:
    def __init__(self, instance_data: Any, label: Union[str, int]):
        self._instance_data = instance_data
        self._label = label

    def data(self):
        return self._instance_data

    def label(self):
        return self._label

    def __repr__(self):
        return f"{self._instance_data}-{self._label}"
```

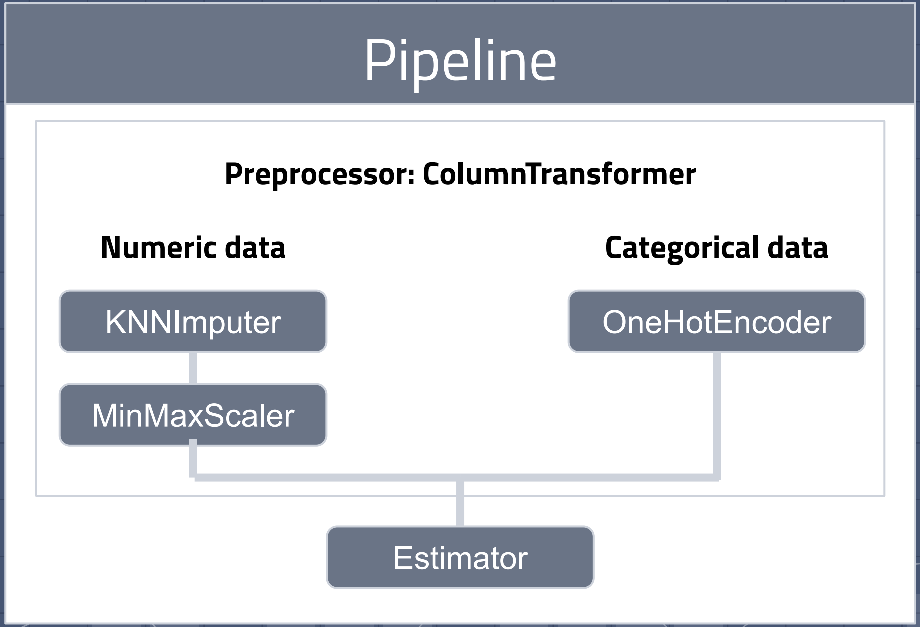
```
def return_dfs(X:pd.DataFrame, y:pd.DataFrame, k:int):
    listt = []
    for i, yy in y.items():
        '''
        cria uma instancia da classe para cada instancia do dataset
        cada instancia possui o index no dataset e a label correspondente
        '''
        listt.append(Instance(i, yy))
    s_folds = stratified_k_folds(listt, k)

    folds = []
    data = []
    labels = []
    for i in range(k):
        '''
        para cada i em k(quantidade de folds) pega o indices que estao no fold
        e utiliza esses indices para montar os fold de dados e de labels
        e em seguida adiciona esse fold criado na lista de todos folds
        '''
        indx = [a._instance_data for a in s_folds[i]]

        folds.append(indx)
        data.append(X.iloc[indx])
        labels.append(y.iloc[indx])

    return data, labels
```

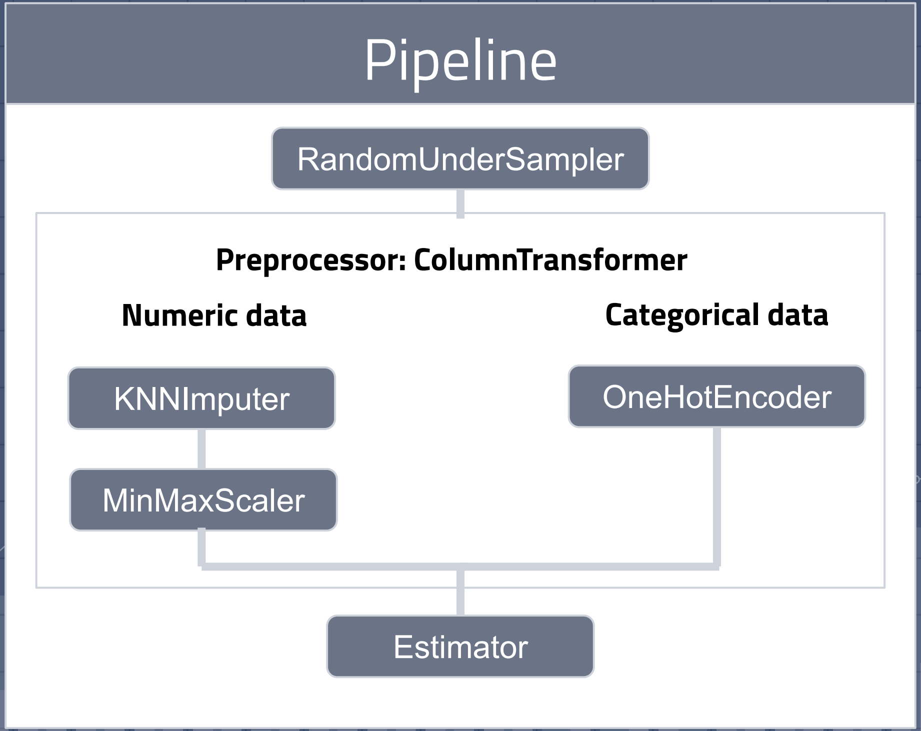
PRÉ PROCESSAMENTO



- Análise empírica
- Análise utilizando matriz de correlação
- Normalização utilizando Min-Max Scaling
- Imputação de valores faltantes usando KNNImputer
- Transforma os valores de um atributo categórico em novos atributos

Pipeline


Pipeline
Preprocessor: ColumnTransformer
Numeric data
Categorical data
KNNImputer
MinMaxScaler
OneHotEncoder
Estimator


Pipeline
RandomUnderSampler
Preprocessor: ColumnTransformer
Numeric data
Categorical data
KNNImputer
MinMaxScaler
OneHotEncoder
Estimator

Pipeline

```
    numeric_features = ["MonthlyCharges", "TotalCharges", "tenure", "gender", "
Partner", "Dependents",
                        "PhoneService", "PaperlessBilling"]
    numeric_transformer = Pipeline(
        steps=[("knnImp", KNNImputer(n_neighbors=3)), ("scaler", MinMaxScaler())]
    )
    categorical_features = ["InternetService", "PaymentMethod", 'MultipleLines',
'OnlineSecurity', 'OnlineBackup',
                            'DeviceProtection', 'TechSupport', 'StreamingMovies',
 'Contract']
    categorical_transformer = Pipeline(
        steps=[("OneHot", OneHotEncoder(handle_unknown="ignore"))]
    )
    preprocessor = ColumnTransformer(
        transformers=[
            ("num", numeric_transformer, numeric_features),
            ("cat", categorical_transformer, categorical_features)
        ]
    )
    if rus:
        pipe = Pipeline(
            steps=[("rus", RandomUnderSampler(random_state=0)), ("pp",
preprocessor), ("clf", clf)]
        )
    else:
        pipe = Pipeline(
            steps=[("pp", preprocessor), ("clf", clf)]
        )

    search = RandomizedSearchCV(pipe, param_grid[i], verbose=True, n_iter=20,
refit=True, random_state=0)
    search.fit(X_train, y_train)

    y_pred = search.predict(X_test)


    y_test = np.array(y_test)

    for metric in ['accuracy', 'precision', 'recall', 'f1measure']:
        if metric not in metadata[run][type(clf).__name__]:
            metadata[run][type(clf).__name__][metric] = {}
    metadata[run][type(clf).__name__]['accuracy'] = accuracy(y_test, y_pred)
    metadata[run][type(clf).__name__]['precision'] = precision(y_test, y_pred)
    metadata[run][type(clf).__name__]['recall'] = recall(y_test, y_pred)
    metadata[run][type(clf).__name__]['f1measure'] = f1Measure(y_test, y_pred)
return metadata
```

PseudoCódigo

Algorithm 1 K-fold Cross Validation

$X, y \leftarrow return\_dfs(data_X, data_y, k)$
$all\_metadata \leftarrow \emptyset$
for $X\_test, y\_test \in X, y$ **do**
    $X\_train \leftarrow X - X\_test$
    $y\_train \leftarrow y - y\_test$
    $metadata \leftarrow Pipeline(X\_train, y\_train, X\_test, y\_test)$
    $all\_metadata \leftarrow all\_metadata \cup metadata$
end for
return $all\_metadata$

ALGORITMOS ESCOLHIDOS

SVM - Support Vector Machine

Algoritmo classificador linear binário não probabilístico. Procura o hiperplano entre dados de duas classes

XGBoost

Algoritmo baseado em árvores de decisão com GradientBoosting.

GaussianNB

Naive Bayes Gaussian.

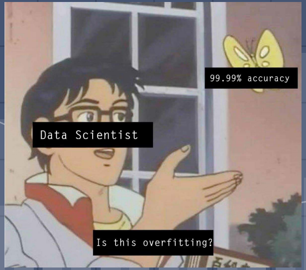
MÉTRICAS

	Desempenho médio	Desvio padrão
Algoritmo 1	10	20
Algoritmo 2	30	15
Algoritmo 3	5	24

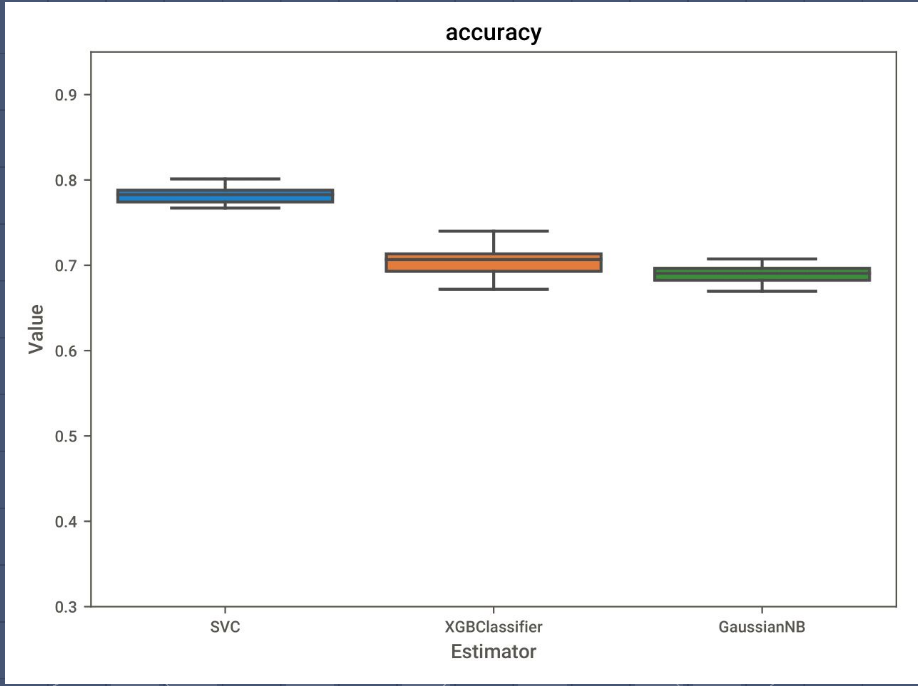
MÉTRICAS (Acurácia e Precisão) - UnderSampling

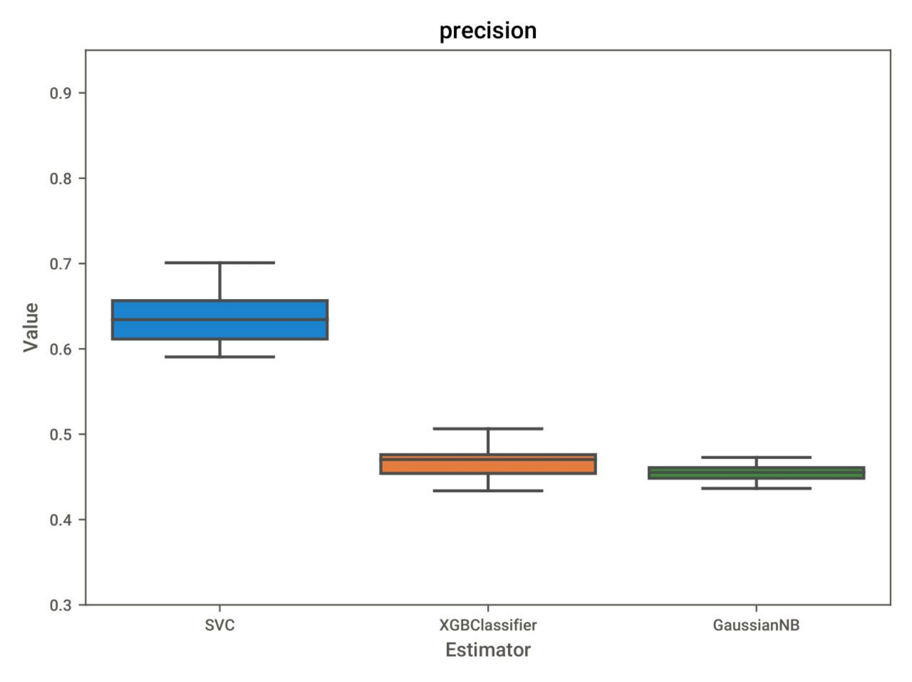
	Desempenho médio	Desvio padrão
SVC	0.782765	0.011507
XGBOOST	0.704531	0.019574
GaussianNB	0.689197	0.012587

	Desempenho médio	Desvio padrão
SVC	0.638734	0.035831
XGBOOST	0.467399	0.020973
GaussianNB	0.454311	0.011943



MÉTRICAS (Acurácia e Precisão) – UnderSampling



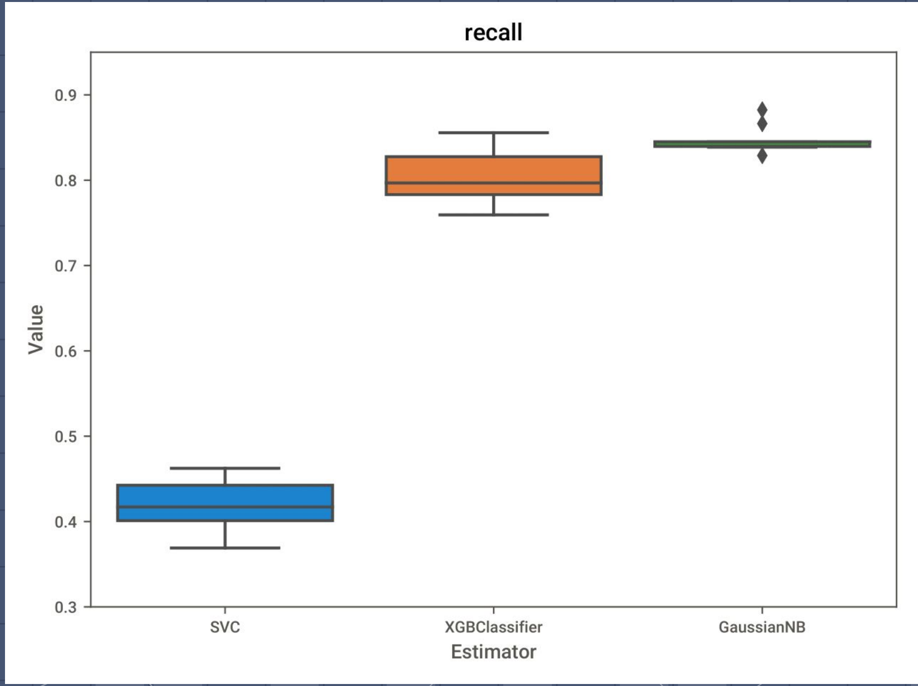


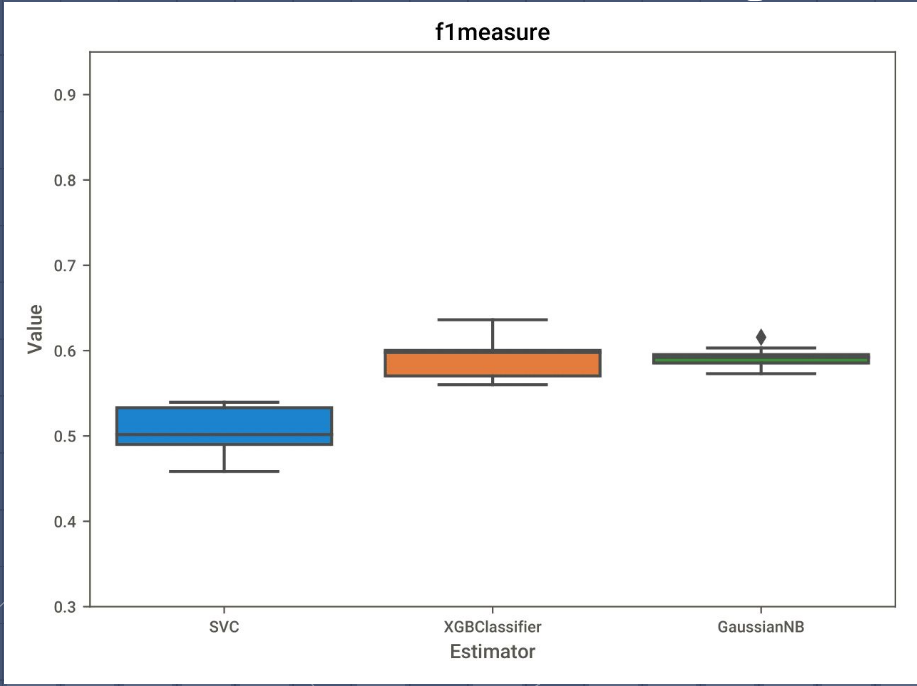
MÉTRICAS (Recall e F1Measure) – UnderSampling

	Desempenho médio	Desvio padrão
SVC	0.419499	0.029269
XGBOOST	0.803631	0.02978
GaussianNB	0.847507	0.015438

	Desempenho médio	Desvio padrão
SVC	0.505901	0.028015
XGBOOST	0.590902	0.023053
GaussianNB	0.591464	0.01246

MÉTRICAS (Recall e F1Measure) – UnderSampling



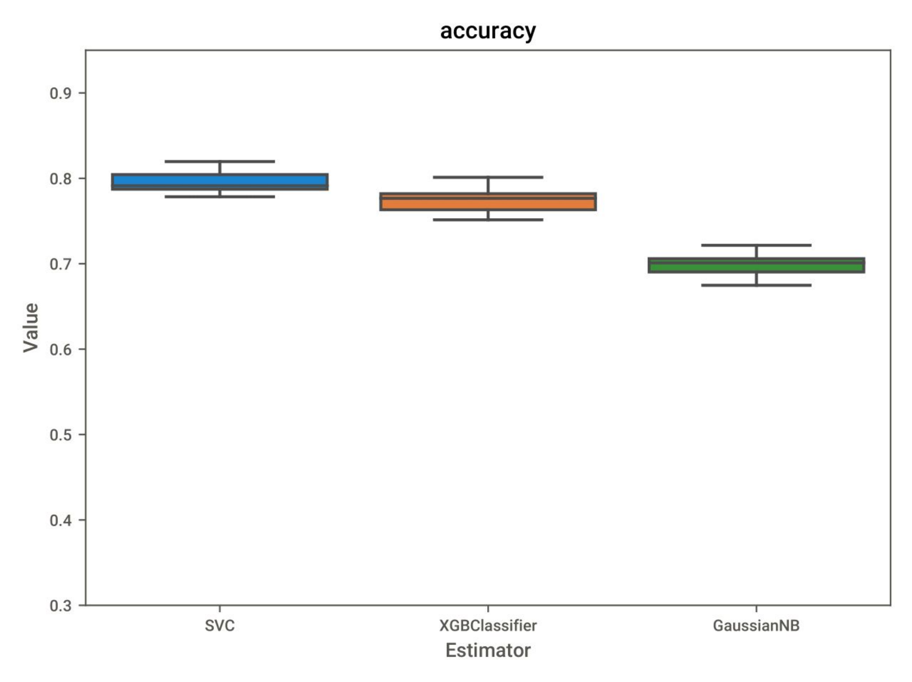


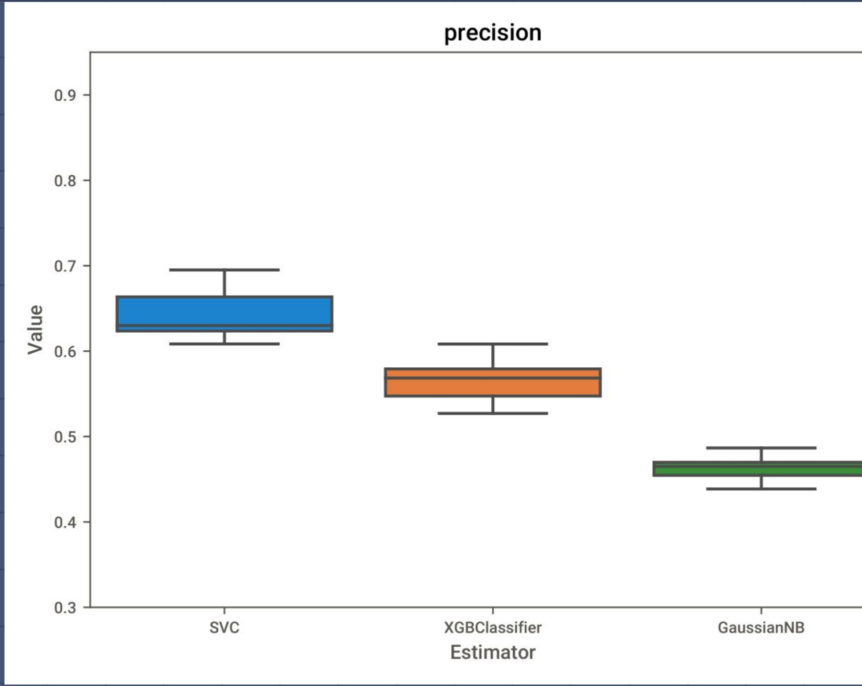
MÉTRICAS (Acurácia e Precisão)

	Desempenho médio	Desvio padrão
SVC	0.795544	0.013279
XGBOOST	0.773534	0.015294
GaussianNB	0.698849	0.013008

	Desempenho médio	Desvio padrão
SVC	0.643444	0.029137
XGBOOST	0.563995	0.02542
GaussianNB	0.46294	0.013204

MÉTRICAS (Acurácia e Precisão)



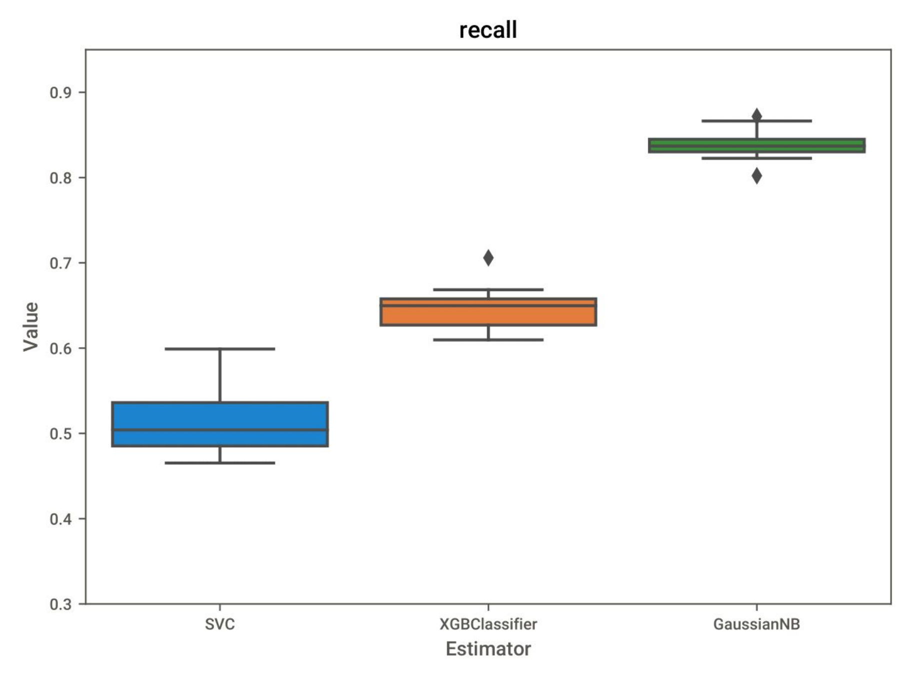


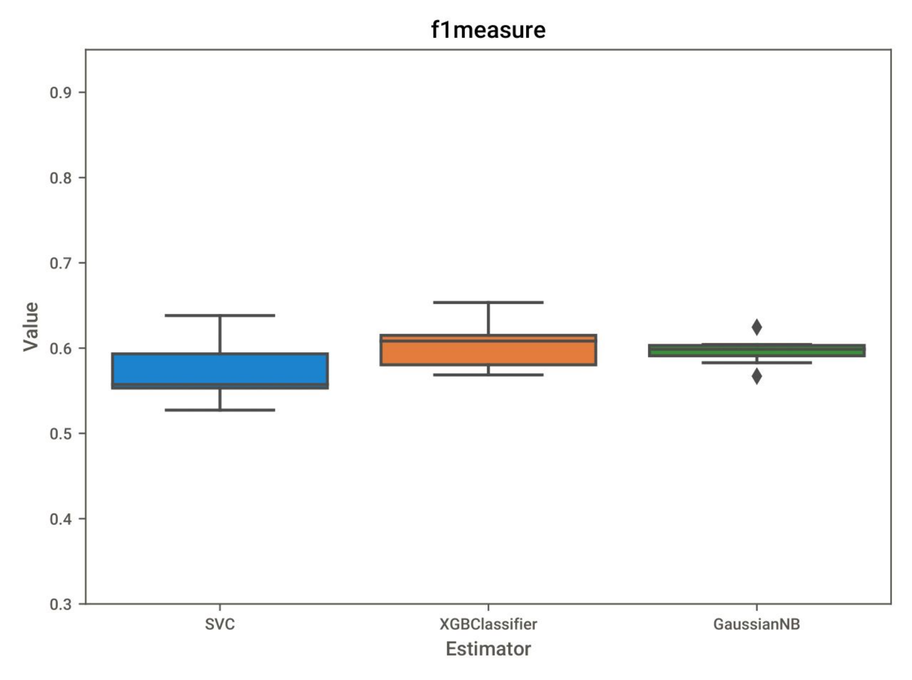
MÉTRICAS (Recall e F1Measure)

	Desempenho médio	Desvio padrão
SVC	0.514174	0.040452
XGBOOST	0.646852	0.028786
GaussianNB	0.838943	0.020164

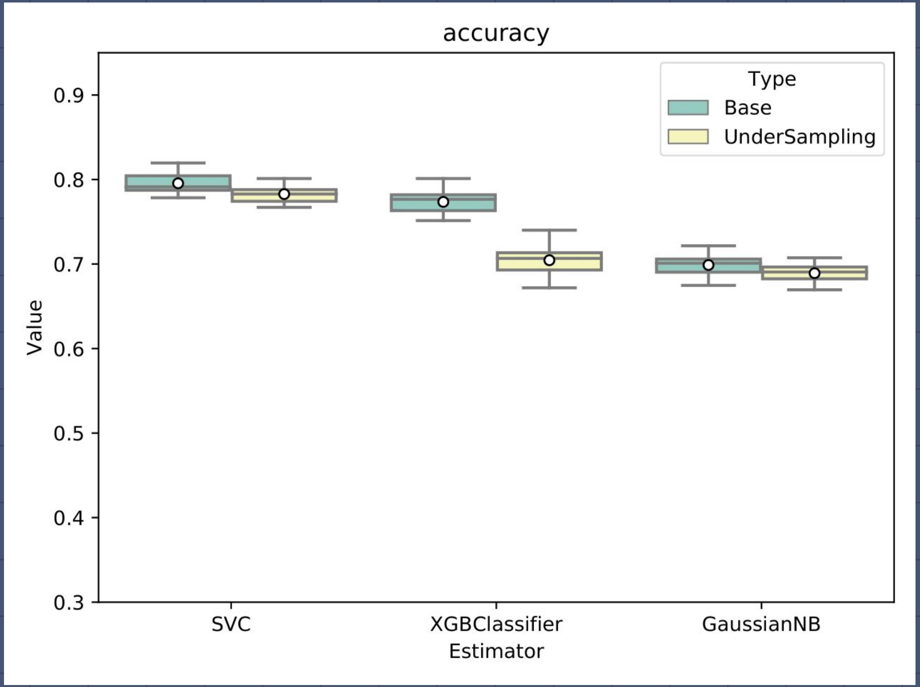
	Desempenho médio	Desvio padrão
SVC	0.571172	0.033598
XGBOOST	0.60254	0.02644
GaussianNB	0.596593	0.015013

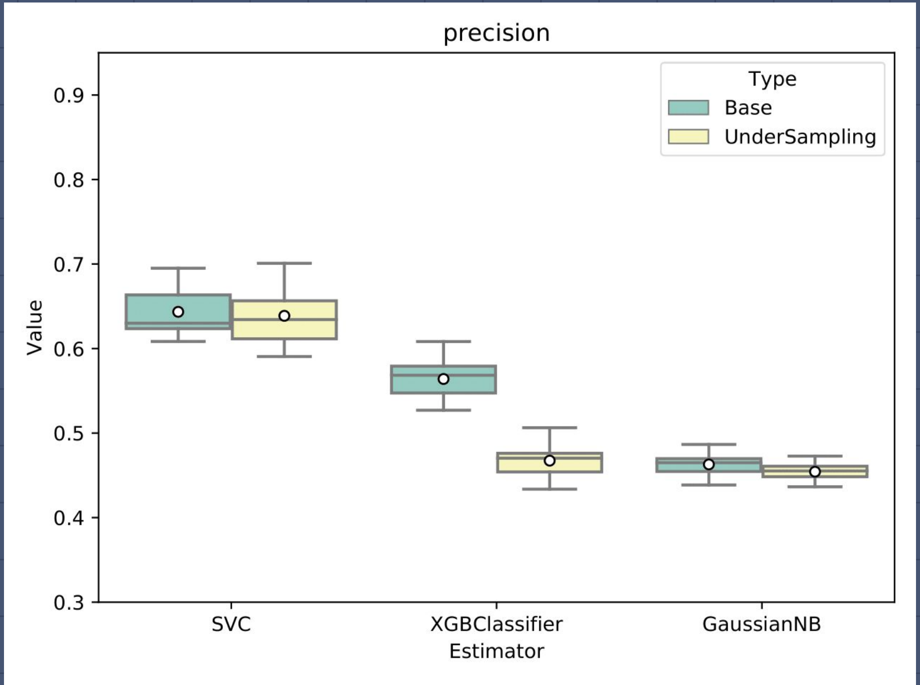
MÉTRICAS (Recall e F1Measure)



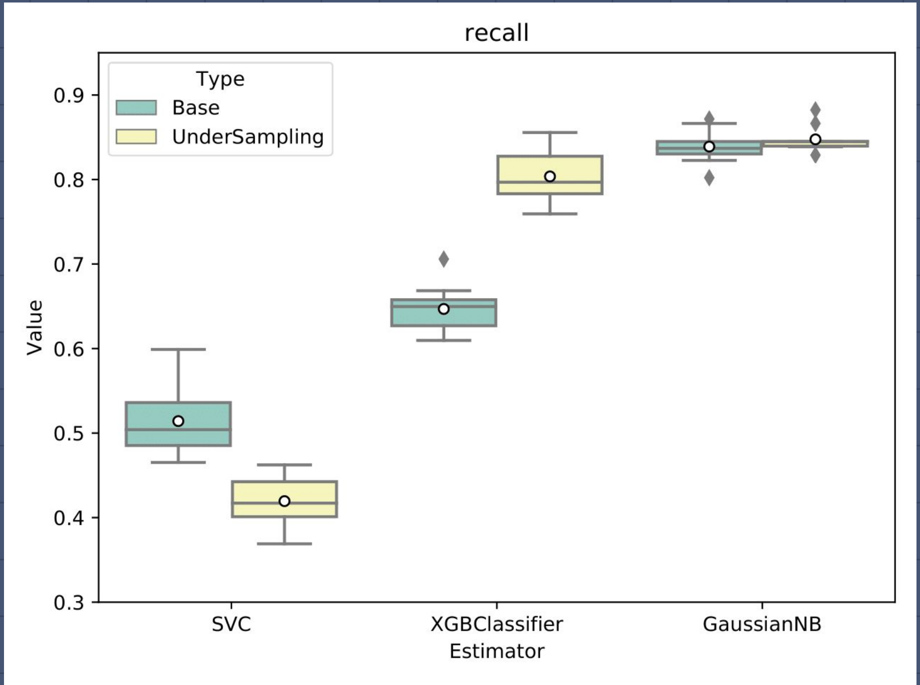


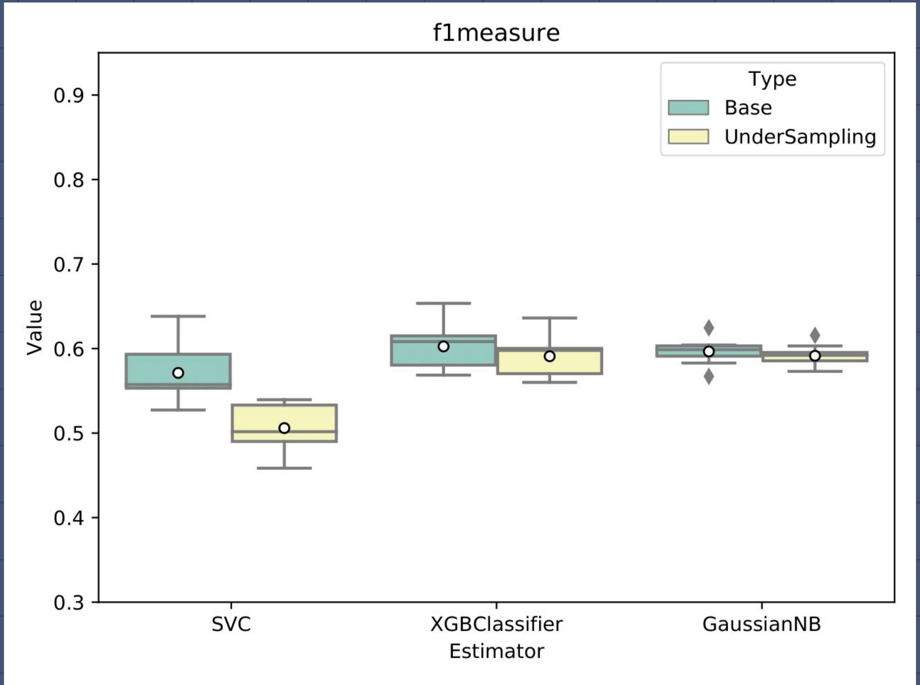
MÉTRICAS (Acurácia e Precisão) – Comparação





MÉTRICAS (Recall e F1Measure) – Comparação





Conclusão

Como o *churn* gera impacto de caráter econômico, acreditamos que a melhor opção de modelo, para este caso, seria o Gaussian Naïve Bayes, pois apresentou o melhor desempenho para **F-measure** e **Recall**.

Acreditamos que a priorização do **Recall** é interessante por priorizar manter os clientes da empresa. E a da **F-measure** por permitir ajuste de parâmetros baseado em características do mercado como custo/retorno de prevenção de *churn*, pois o quanto é interessante poupar caixa da empresa (**reduzir FP**) ou aumentar a arrecadação mantendo clientes (**reduzir FN**) pode variar de acordo com as condições de mercado e custos de aquisição ou manutenção de cliente.

Obrigado!

Perguntas?