

Klasyfikacja niezbalansowana, klasyfikatory zespołowe i wyjaśnialna AI

Wykorzystanie Google Colab

Jeśli korzystasz z Google Colab skopiuj plik `feature_names.json` do katalogu głównego projektu.



Ładowanie i eksploracja danych

Na tym laboratorium wykorzystamy zbiór danych [Polish companies bankruptcy](#). Dotyczy on klasyfikacji, na podstawie danych z raportów finansowych, czy firma zbankrutuje w ciągu najbliższych kilku lat. Jest to zadanie szczególnie istotne dla banków, funduszy inwestycyjnych, firm ubezpieczeniowych itp., które z tego powodu zatrudniają licznie data scientistów. Zbiór zawiera 64 cechy, obliczone przez ekonomistów, którzy stworzyli ten zbiór, są one opisane na podlinkowanej wcześniej stronie. Dotyczą one zysków, posiadanych zasobów oraz długów firm.

Ściągnij i rozpakuj dane (`Data Folder` -> `data.zip`) do katalogu `data` obok tego notebooka. Znajduje się tam 5 plików w formacie `.arff`, wykorzystywanym głównie przez oprogramowanie Weka. Jest to program do "klikania" ML w interfejsie graficznym, jakiś czas temu popularny wśród mniej technicznych data scientistów. W Pythonie łąduje się je za pomocą bibliotek SciPy i Pandas.

Jeśli korzystasz z Linuksa możesz skorzystać z poniższych poleceń do pobrania i rozpakowania tych plików.

```
In [ ]: # !mkdir -p data
        # !wget https://archive.ics.uci.edu/static/public/365/polish+companies+ba
```

```
In [ ]: # !unzip data/data.zip -d data
```

W dalszej części laboratorium wykorzystamy plik `3year.arff`, w którym na podstawie finansowych firmy po 3 latach monitorowania chcemy przewidywać, czy firma zbankrutuje w ciągu najbliższych 3 lat. Jest to dość realistyczny horyzont czasowy.

Dodatkowo w pliku `feature_names.json` znajdują się nazwy cech. Są bardzo długie, więc póki co nie będziemy z nich korzystać.

```
In [ ]: import json
        import os
```

```

from scipy.io import arff
import pandas as pd

data = arff.loadarff(os.path.join("data", "3year.arff"))

with open("feature_names.json") as file:
    feature_names = json.load(file)

X = pd.DataFrame(data[0])

```

Przyjrzyjmy się teraz naszym danym.

In []: `X.head()`

Out []:

	Attr1	Attr2	Attr3	Attr4	Attr5	Attr6	Attr7	Attr8	Attr9
0	0.174190	0.41299	0.14371	1.3480	-28.9820	0.60383	0.219460	1.1225	1.190
1	0.146240	0.46038	0.28230	1.6294	2.5952	0.00000	0.171850	1.1721	1.60
2	0.000595	0.22612	0.48839	3.1599	84.8740	0.19114	0.004572	2.9881	1.00
3	0.024526	0.43236	0.27546	1.7833	-10.1050	0.56944	0.024526	1.3057	1.05
4	0.188290	0.41504	0.34231	1.9279	-58.2740	0.00000	0.233580	1.4094	1.33

5 rows x 65 columns

In []: `X.dtypes`

Out []:

```

Attr1      float64
Attr2      float64
Attr3      float64
Attr4      float64
Attr5      float64
...
Attr61     float64
Attr62     float64
Attr63     float64
Attr64     float64
class      object
Length: 65, dtype: object

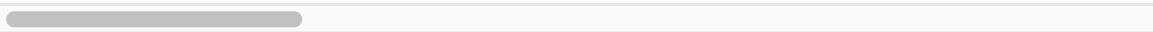
```

In []: `X.describe()`

Out []:

	Attr1	Attr2	Attr3	Attr4	Attr5
count	10503.000000	10503.000000	10503.000000	10485.000000	1.047800e+04
mean	0.052844	0.619911	0.095490	9.980499	-1.347662e+03
std	0.647797	6.427041	6.420056	523.691951	1.185806e+05
min	-17.692000	0.000000	-479.730000	0.002080	-1.190300e+07
25%	0.000686	0.253955	0.017461	1.040100	-5.207075e+01
50%	0.043034	0.464140	0.198560	1.605600	1.579300e+00
75%	0.123805	0.689330	0.419545	2.959500	5.608400e+01
max	52.652000	480.730000	17.708000	53433.000000	6.854400e+05

8 rows × 64 columns



In []:

feature_names

```

Out[ ]: ['net profit / total assets',
        'total liabilities / total assets',
        'working capital / total assets',
        'current assets / short-term liabilities',
        '[(cash + short-term securities + receivables - short-term liabilities)
 / (operating expenses - depreciation)] * 365',
        'retained earnings / total assets',
        'EBIT / total assets',
        'book value of equity / total liabilities',
        'sales / total assets',
        'equity / total assets',
        '(gross profit + extraordinary items + financial expenses) / total asse
ts',
        'gross profit / short-term liabilities',
        '(gross profit + depreciation) / sales',
        '(gross profit + interest) / total assets',
        '(total liabilities * 365) / (gross profit + depreciation)',
        '(gross profit + depreciation) / total liabilities',
        'total assets / total liabilities',
        'gross profit / total assets',
        'gross profit / sales',
        '(inventory * 365) / sales',
        'sales (n) / sales (n-1)',
        'profit on operating activities / total assets',
        'net profit / sales',
        'gross profit (in 3 years) / total assets',
        '(equity - share capital) / total assets',
        '(net profit + depreciation) / total liabilities',
        'profit on operating activities / financial expenses',
        'working capital / fixed assets',
        'logarithm of total assets',
        '(total liabilities - cash) / sales',
        '(gross profit + interest) / sales',
        '(current liabilities * 365) / cost of products sold',
        'operating expenses / short-term liabilities',
        'operating expenses / total liabilities',
        'profit on sales / total assets',
        'total sales / total assets',
        'constant capital / total assets',
        'profit on sales / sales',
        '(current assets - inventory - receivables) / short-term liabilities',
        'total liabilities / ((profit on operating activities + depreciation) *
(12/365))',
        'profit on operating activities / sales',
        'rotation receivables + inventory turnover in days',
        '(receivables * 365) / sales',
        'net profit / inventory',
        '(current assets - inventory) / short-term liabilities',
        '(inventory * 365) / cost of products sold',
        'EBITDA (profit on operating activities - depreciation) / total asset
s',
        'EBITDA (profit on operating activities - depreciation) / sales',
        'current assets / total liabilities',
        'short-term liabilities / total assets',
        '(short-term liabilities * 365) / cost of products sold)',
        'equity / fixed assets',
        'constant capital / fixed assets',
        'working capital',
        '(sales - cost of products sold) / sales',
        '(current assets - inventory - short-term liabilities) / (sales - gross

```

```
profit - depreciation)',  
'total costs / total sales',  
'long-term liabilities / equity',  
'sales / inventory',  
'sales / receivables',  
'(short-term liabilities * 365) / sales',  
'sales / short-term liabilities',  
'sales / fixed assets']
```

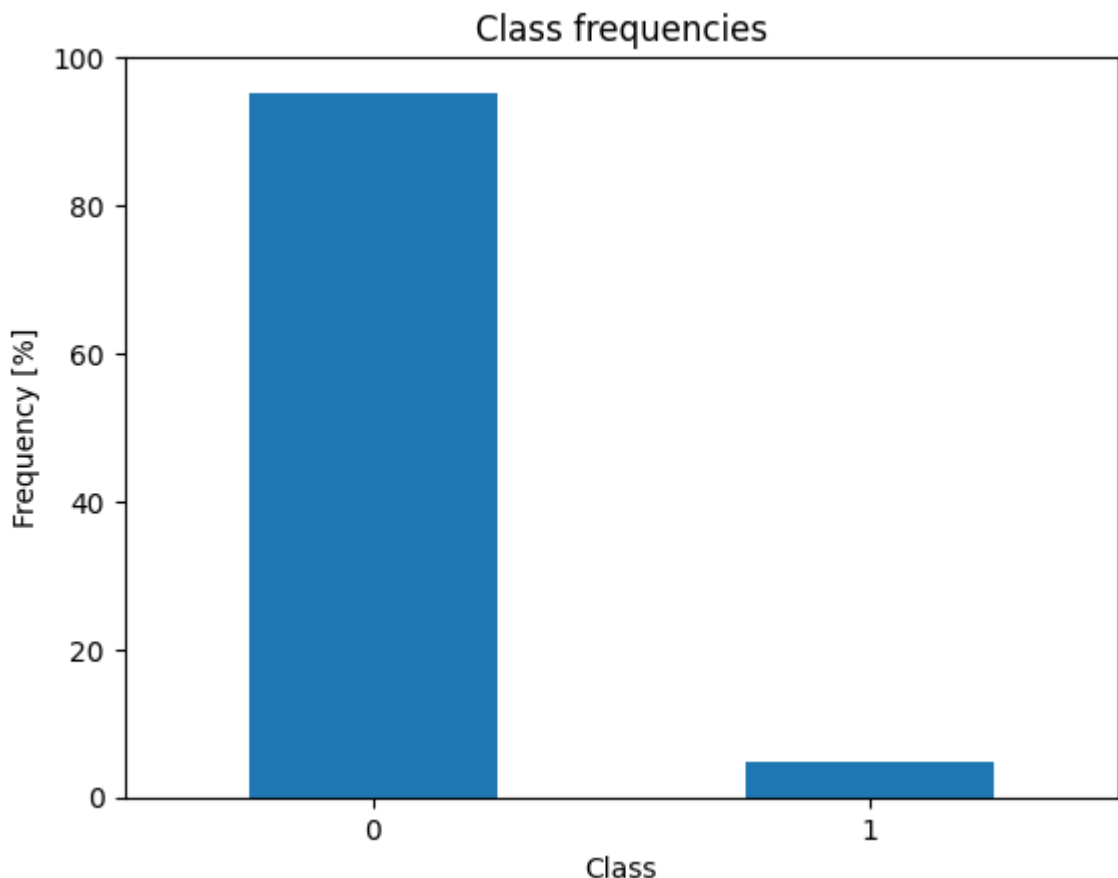
DataFrame zawiera 64 atrybuty numeryczne o zróżnicowanych rozkładach wartości oraz kolumnę "class" typu bytes z klasami 0 i 1. Wiemy, że mamy do czynienia z klasyfikacją binarną - klasa 0 to brak bankructwa, klasa 1 to bankructwo w ciągu najbliższych 3 lat. Przyjrzyjmy się dokładniej naszym danym.

Zadanie 1 (0.5 punktu)

1. Wyodrębnij klasy jako osobną zmienną typu `pd.Series`, usuwając je z macierzy `X`. Przekonwertuj go na liczby całkowite.
2. Narysuj wykres słupkowy (bar plot) częstotliwości obu klas w całym zbiorze. Upewnij się, że na osi X są numery lub nazwy klas, a oś Y ma wartości w procentach.

```
In [ ]: y = X.pop("class").astype("uint8")
```

```
In [ ]: ax = (y.value_counts(normalize=True) * 100).plot.bar(  
    title="Class frequencies",  
    ylabel="Frequency [%]",  
    xlabel="Class",  
    rot=0  
)
```



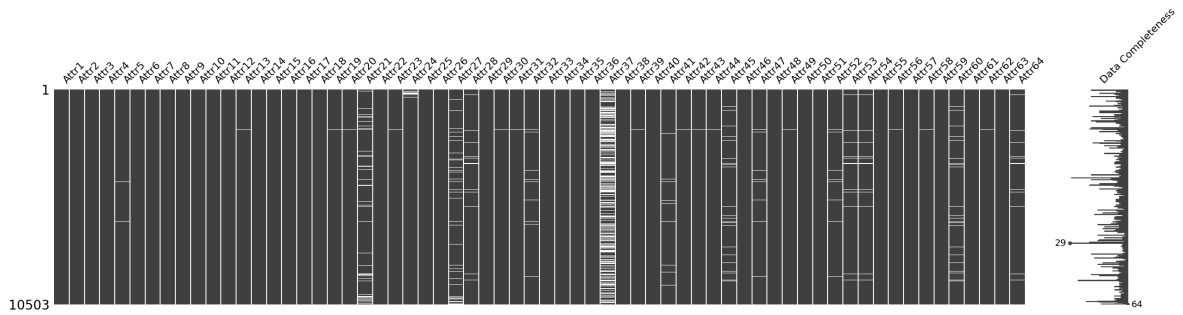
Jak widać, klasa pozytywna jest w znacznej mniejszości, stanowi poniżej 5% zbioru. Taki problem nazywamy **klasyfikacją niezbilansowaną (imbalanced classification)**. Mamy tu **klasę dominującą (majority class)** oraz **klasę mniejszościową (minority class)**. Pechowo prawie zawsze interesuje nas ta druga, bo klasa większościowa jest trywialna. Przykładowo, 99% badanych jest zdrowych, a 1% ma niewykryty nowotwór - z oczywistych przyczyn chcemy wykrywać właśnie sytuację rzadką (problem diagnozy jako klasyfikacji jest zasadniczo zawsze niezbilansowany). W dalszej części laboratorium poznamy szereg konsekwencji tego zjawiska i metody na radzenie sobie z nim.

Mamy sporo cech, wszystkie numeryczne. Ciekawe, czy mają wartości brakujące, a jeśli tak, to ile. Można to policzyć, ale wykres jest często czytelniejszy. Pomoże nam tu biblioteka `missingno`. Zaznacza ona w każdej kolumnie wartości brakujące przeciwnym kolorem.

```
In [ ]: import missingno as msno

msno.matrix(X, labels=True, figsize=(30, 6))
```

```
Out[ ]: <Axes: >
```



Jak widać, cecha 37 ma bardzo dużo wartości brakujących, podczas gdy pozostałe cechy mają raczej niewielką ich liczbę. W takiej sytuacji najlepiej usunąć tę cechę, a pozostałe wartości brakujące **uzupełnić / imputować (impute)**. Typowo wykorzystuje się do tego wartość średnią lub medianę z danej kolumny. Ale uwaga - imputacji dokonuje się dopiero po podziale na zbiór treningowy i testowy! W przeciwnym wypadku wykorzystywalibyśmy dane ze zbioru testowego, co sztucznie zawyżyłoby wyniki. Jest to błąd metodologiczny - **wyciek danych (data leakage)**.

Podział na zbiór treningowy i testowy to pierwszy moment, kiedy niezbalansowanie danych nam przeszkadza. Jeżeli zrobimy to czysto losowo, to są spore szanse, że w zbiorze testowym będzie tylko klasa negatywna - w końcu jest jej aż >95%. Dlatego wykorzystuje się **próbkiowanie ze stratyfikacją (stratified sampling)**, dzięki któremu proporcje klas w zbiorze przed podziałem oraz obu zbiorach po podziale są takie same.

Zadanie 2 (0.75 punktu)

1. Usuń kolumnę "Attr37" ze zbioru danych.
2. Dokonaj podziału zbioru na treningowy i testowy w proporcjach 80%-20%, z przemieszaniem (`shuffle`), ze stratyfikacją, wykorzystując funkcję `train_test_split` ze Scikit-learn'a.
3. Uzupełnij wartości brakujące średnią wartością cechy z pomocą klasy `SimpleImputer`.

Uwaga:

- pamiętaj o uwzględnieniu stałego `random_state=0`, aby wyniki były **reprodukowalne (reproducible)**
- `stratify` oczekuje wektora klas
- wartości do imputacji trzeba wyestymować na zbiorze treningowym (`.fit()`), a potem zastosować te nauczone wartości na obu podzbiorach (treningowym i testowym)

```
In [ ]: X = X.drop("Attr37", axis="columns")
```

```
In [ ]: from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, shuffle=True, stratify=y, random_state=0
)
```

```
In [ ]: from sklearn.impute import SimpleImputer
        from sklearn.pipeline import Pipeline
        import warnings

        warnings.filterwarnings("ignore")

        pipeline = Pipeline([ ("mean_imputer", SimpleImputer()) ])
        X_train = pipeline.fit_transform(X_train)
        X_test = pipeline.transform(X_test)

        warnings.filterwarnings("default")
```

Prosta klasyfikacja

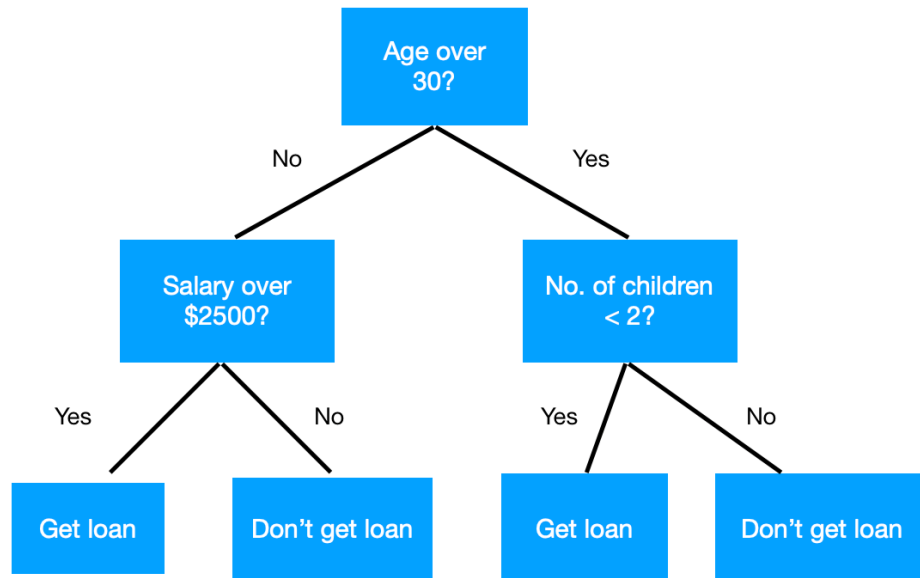
Zanim przejdzie się do modeli bardziej złożonych, trzeba najpierw wypróbować coś prostego, żeby mieć punkt odniesienia. Tworzy się dlatego **modele bazowe (baselines)**.

W naszym przypadku będzie to **drzewo decyzyjne (decision tree)**. Jest to drzewo binarne z decyzjami if-else, prowadzącymi do klasyfikacji danego przykładu w liściu. Każdy podział w drzewie to pytanie postaci "Czy wartość cechy X jest większa lub równa Y?". Trening takiego drzewa to prosty algorytm zachłanny, bardzo przypomina budowę zwykłego drzewa binarnego. W każdym węźle wykonujemy:

1. Sprawdź po kolei wszystkie możliwe punkty podziału, czyli każdą (unikalną) wartość każdej cechy, po kolei.
2. Dla każdego przypadku podziel zbiór na 2 kawałki: niespełniający warunku (lewe dziecko) i spełniający warunek (prawe dziecko).
3. Oblicz jakość podziału według pewnej wybranej funkcji jakości. Im lepiej nasz if/else rozdziela klasy od siebie (im "czystsze" są węzły-dzieci), tym wyższa jakość. Innymi słowy, chcemy, żeby do jednego dziecka poszła jedna klasa, a do drugiego druga.
4. Wybierz podział o najwyższej jakości.

Taki algorytm wykonuje się rekurencyjnie, aż otrzymamy węzeł czysty (pure leaf), czyli taki, w którym są przykłady z tylko jednej klasy. Typowo wykorzystywaną funkcją jakości (kryterium podziału) jest entropia Shannona - im niższa entropia, tym bardziej jednolite są klasy w węźle (czyli wybieramy podział o najniższej entropii).

Powyższe wytłumaczenie algorytmu jest oczywiście nieformalne i dość skrótowe. Doskonałe tłumaczenie, z interaktywnymi wizualizacjami, dostępne jest [tutaj](#). W formie filmów - [tutaj](#) oraz [tutaj](#). Dla drzew do regresji - [ten film](#).



Warto zauważyć, że taka konstrukcja prowadzi zawsze do overfittingu. Otrzymanie liści czystych oznacza, że mamy 100% dokładności na zbiorze treningowym, czyli perfekcyjnie przeuczony klasyfikator. W związku z tym nasze predykcje mają bardzo niski bias, ale bardzo dużą wariancję. Pomimo tego drzewa potrafią dać bardzo przyzwoite wyniki, a w celu ich poprawy można je regularyzować, aby mieć mniej "rozrośnięte" drzewo. [Film dla zainteresowanych](#).

W tym wypadku AI to naprawdę tylko zbiór if'ów ;)

Mając wytrenowany klasyfikator, trzeba oczywiście sprawdzić, jak dobrze on sobie radzi. Tu natrafiamy na kolejny problem z klasyfikacją niezbalansowaną - zwykła celność (accuracy) na pewno nie zadziała! Typowo wykorzystuje się AUC, nazywane też AUROC (Area Under Receiver Operating Characteristic), bo metryka ta "widzi" i uwzględnia niezbalansowanie klas. Wymaga ona przekazania prawdopodobieństwa klasy pozytywnej, a nie tylko binarnej decyzji.

Bardzo dobre i bardziej szczegółowe wytłumaczenie, z interaktywnymi wizualizacjami, można znaleźć [tutaj](#). Dla preferujących filmy - [tutaj](#).

Co ważne, z definicji AUROC, trzeba tam użyć prawdopodobieństw klasy pozytywnej (klasy 1). W Scikit-learn'ie zwraca je metoda `.predict_proba()`, która w kolejnych kolumnach zwraca prawdopodobieństwa poszczególnych klas.

Zadanie 3 (0.75 punktu)

1. Wytrenuj klasyfikator drzewa decyzyjnego (klasa `DecisionTreeClassifier`). Użyj entropii jako kryterium podziału.
2. Oblicz i wypisz AUROC na zbiorze testowym dla drzewa decyzyjnego (funkcja `roc_auc_score`).

3. Skomentuj wynik - czy twoim zdaniem osiągnięty AUROC to dużo czy mało, biorąc pod uwagę możliwy zakres wartości tej metryki?

Uwaga:

- pamiętaj o użyciu stałego `random_state=0`

```
In [ ]: from sklearn.tree import DecisionTreeClassifier

dt_clf = DecisionTreeClassifier(criterion="entropy", random_state=0)
dt_clf = dt_clf.fit(X_train, y_train)
```

```
In [ ]: from sklearn.metrics import roc_auc_score

y_probabilities = dt_clf.predict_proba(X_test)
auroc           = roc_auc_score(y_test, y_probabilities[:, 1])
print("AUROC:", auroc)
```

AUROC: 0.7266899766899767

Komentarz

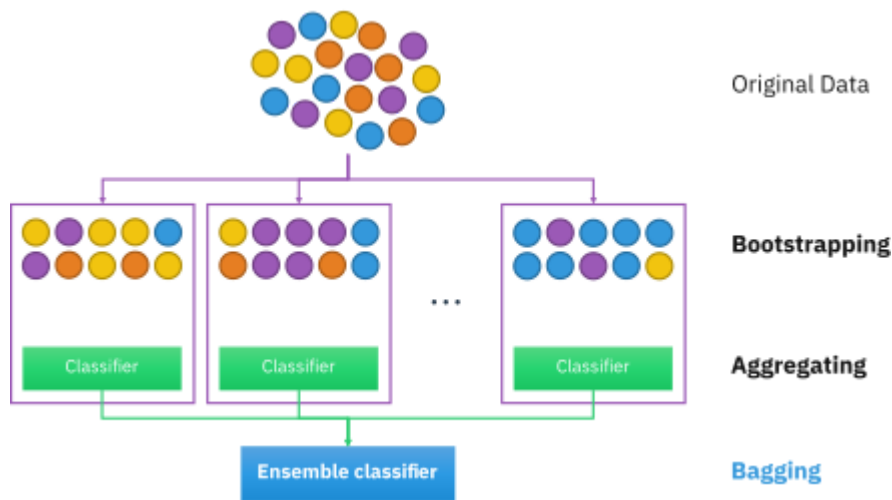
Otrzymaliśmy AUROC na poziomie ~ 0.72 . Wynik jest przeciętny, ponieważ dla losowego klasyfikatora otrzymalibyśmy 0.5, a dla wzorcowego 1.

Uczenie zespołowe, bagging, lasy losowe

Bardzo często wiele klasyfikatorów działających razem daje lepsze wyniki niż pojedynczy klasyfikator. Takie podejście nazywa się **uczeniem zespołowym (ensemble learning)**. Istnieje wiele różnych podejść do tworzenia takich klasyfikatorów złożonych (ensemble classifiers).

Podstawową metodą jest **bagging**:

1. Wylosuj N (np. 100, 500, ...) próbek bootstrapowych (bootstrap sample) ze zbioru treningowego. Próbką bootstrapowa to po prostu losowanie ze zwracaniem, gdzie dla wejściowego zbioru z M wierszami losujemy M próbek. Będą tam powtórzenia, średnio nawet $1/3$, ale się tym nie przejmujemy.
2. Wytrenuj klasyfikator bazowy (base classifier) na każdej z próbek bootstrapowych.
3. Stwórz klasyfikator złożony poprzez uśrednienie predykcji każdego z klasyfikatorów bazowych.



Typowo klasyfikatory bazowe są bardzo proste, żeby można było szybko wytrenować ich dużą liczbę. Prawie zawsze używa się do tego drzew decyzyjnych. Dla klasyfikacji uśrednienie wyników polega na głosowaniu – dla nowej próbki każdy klasyfikator bazowy ją klasyfikuje, sumuje się głosy na każdą klasę i zwraca najbardziej popularną decyzję.

Taki sposób ensemblingu zmniejsza wariancję klasyfikatora. Intuicyjnie, skoro coś uśredniamy, to siłą rzeczy będzie mniej rozrzucone, bo dużo ciężiej będzie osiągnąć jakąś skrajność. Redukuje to też overfitting.

Lasy losowe (Random Forests) to ulepszenie baggingu. Zaobserwowano, że pomimo losowania próbek bootstrapowych, w baggingu poszczególne drzewa są do siebie bardzo podobne (są skorelowane), używają podobnych cech ze zbioru. My natomiast chcemy zróżnicowania, żeby mieć niski bias – redukcją wariancji zajmuje się uśrednianie. Dlatego używa się metody losowej podprzestrzeni (random subspace method) – przy każdym podziale drzewa losuje się tylko pewien podzbiór cech, których możemy użyć do tego podziału. Typowo jest to pierwiastek kwadratowy z ogólnej liczby cech.

Zarówno bagging, jak i lasy losowe mają dodatkowo bardzo przyjemną własność – są mało czułe na hiperparametry, szczególnie na liczbę drzew. W praktyce wystarczy ustawić 500 czy 1000 drzew i będzie dobrze działać. Dalsze dostrajanie hiperparametrów może jeszcze trochę poprawić wyniki, ale nie tak bardzo, jak przy innych klasyfikatorach. Jest to zatem doskonały wybór domyślny, kiedy nie wiemy, jakiego klasyfikatora użyć.

Dodatkowo jest to problem **embarrassingly parallel** – drzewa można trenować w 100% równolegle, dzięki czemu jest to dodatkowo wydajna obliczeniowo metoda.

Głębsze wytłumaczenie, z interaktywnymi wizualizacjami, można znaleźć [tutaj](#). Dobrze tłumaczy je też [ta seria filmów](#).

Zadanie 4 (0.5 punktu)

1. Wytrenuj klasyfikator Random Forest (klasa `RandomForestClassifier`). Użyj 500 drzew i entropii jako kryterium podziału.

2. Sprawdź AUROC na zbiorze testowym.
3. Skomentuj wynik w odniesieniu do drzewa decyzyjnego.

Uwaga: pamiętaj o ustawieniu `random_state=0` . Dla przyspieszenia ustaw `n_jobs=-1` (użyj tylu procesów, ile masz dostępnych rdzeni procesora).

```
In [ ]: from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier(500, criterion="entropy", n_jobs=-1, random_state=0)
rf_clf = rf_clf.fit(X_train, y_train)

In [ ]: y_probabilities = rf_clf.predict_proba(X_test)
auroc = roc_auc_score(y_test, y_probabilities[:, 1])
print("AUROC:", auroc)
```

AUROC: 0.8994111948657404

Komentarz

Klasyfikator wykorzystujący losowe lasy jest zdecydowanie bardziej dokładny niż drzewo decyzyjne, nie jest także bardzo złożony obliczeniowo, więc zyskaliśmy dużo lepszy wynik, relatywnie małym nakładem czasowym.

Jak zobaczymy poniżej, wynik ten możemy jednak jeszcze ulepszyć!

Oversampling, SMOTE

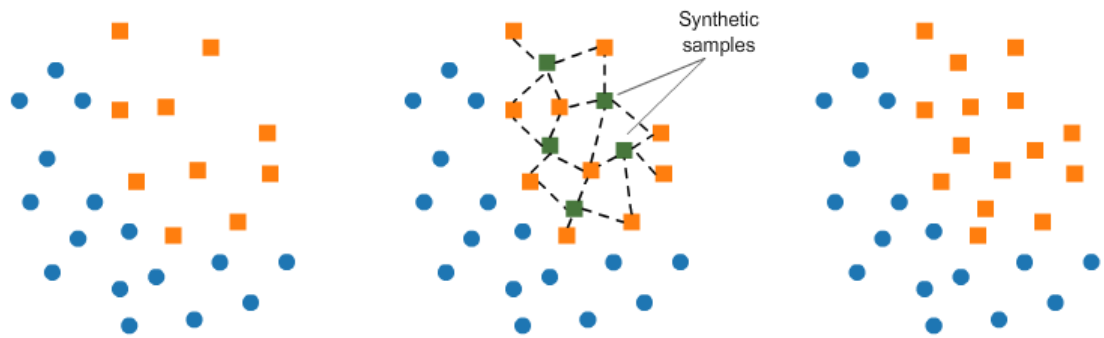
W przypadku zbiorów niezbalansowanych można dokonać **balansowania (balancing)** zbioru. Są tutaj 2 metody:

- **undersampling**: usunięcie przykładów z klasy dominującej
- **oversampling**: wygenerowanie dodatkowych przykładów z klasy mniejszościowej

Undersampling działa dobrze, kiedy niezbalansowanie jest niewielkie, a zbiór jest duży (możemy sobie pozwolić na usunięcie jego części). Oversampling typowo daje lepsze wyniki, istnieją dla niego bardzo efektywne algorytmy. W przypadku bardzo dużego niezbalansowania można zrobić oba.

Typowym algorytmem oversamplingu jest **SMOTE (Synthetic Minority Oversampling Technique)**. Działa on następująco:

1. Idź po kolei po przykładach z klasy mniejszościowej
2. Znajdź `k` najbliższych przykładów dla próbki, typowo `k=5`
3. Wylosuj tylu sąsiadów, ile trzeba do oversamplingu, np. jeżeli chcemy zwiększyć klasę mniejszościową 3 razy (o 200%), to wylosuj 2 z 5 sąsiadów
4. Dla każdego z wylosowanych sąsiadów wylosuj punkt na linii prostej między próbką a tym sąsiadem. Dodaj ten punkt jako nową próbkę do zbioru



Taka technika generuje przykłady bardzo podobne do prawdziwych, więc nie zaburza zbioru, a jednocześnie pomaga klasyfikatorom, bo "zagęszcza" przestrzeń, w której znajduje się klasa pozytywna.

Algorytm SMOTE, jego warianty i inne algorytmy dla problemów niezbalansowanych implementuje biblioteka Imbalanced-learn.

Zadanie 5 (1 punkt)

Użyj SMOTE do zbalansowania zbioru treningowego (nie używa się go na zbiorze testowym!) (klasa `SMOTE`). Wytrenuj drzewo decyzyjne oraz las losowy na zbalansowanym zbiorze, użyj tych samych argumentów co wcześniej. Pamiętaj o użyciu wszędzie stałego `random_state=0` i `n_jobs=-1`. Skomentuj wynik.

```
In [ ]: from imblearn.over_sampling import SMOTE
import warnings

warnings.filterwarnings("ignore")

smote = SMOTE(n_jobs=-1, random_state=0)
X_train_balanced, y_train_balanced = smote.fit_resample(X_train, y_train)

warnings.filterwarnings("default")

In [ ]: # Decision Tree
dt_clf = DecisionTreeClassifier(criterion="entropy", random_state=0)
dt_clf = dt_clf.fit(X_train_balanced, y_train_balanced)
y_probabilities = dt_clf.predict_proba(X_test)
auroc = roc_auc_score(y_test, y_probabilities[:, 1])
print("AUROC DTC:", auroc)

# Random Forest
rf_clf = RandomForestClassifier(500, criterion="entropy", n_jobs=-1)
rf_clf = rf_clf.fit(X_train_balanced, y_train_balanced)
y_probabilities = rf_clf.predict_proba(X_test)
auroc = roc_auc_score(y_test, y_probabilities[:, 1])
print("AUROC RFC:", auroc)
```

```
AUROC DTC: 0.70995670995671
AUROC RFC: 0.9047644274917003
```

Komentarz

Zastosowanie oversamplingu pogorszyło lub polepszyło nieznacznie wyniki dla odpowiednio drzewa decyzyjnego i losowego lasu.

W dalszej części laboratorium używaj zbioru po zastosowaniu SMOTE do treningu klasyfikatorów.

Dostrajanie (tuning) hiperparametrów

Lasy losowe są stosunkowo mało czułe na dobór hiperparametrów - i dobrze, bo mają ich dość dużo. Można zawsze jednak spróbować to zrobić, a w szczególności najważniejszy jest parametr `max_features`, oznaczający, ile cech losować przy każdym podziale drzewa. Typowo sprawdza się wartości z zakresu `[0.1, 0.5]`.

W kwestii szybkości, kiedy dostrajamy hiperparametry, to mniej oczywiste jest, jakiego `n_jobs` użyć. Z jednej strony klasyfikator może być trenowany na wielu procesach, a z drugiej można trenować wiele klasyfikatorów na różnych zestawach hiperparametrów równolegle. Jeżeli nasz klasyfikator bardzo dobrze się uwspółbieżnia (jak Random Forest), to można dać mu nawet wszystkie rdzenie, a za to wypróbowywać kolejne zestawy hiperparametrów sekwencyjnie. Warto ustawić parametr `verbose` na 2 lub więcej, żeby dostać logi podczas długiego treningu i zmierzyć czas wykonania. W praktyce ustawia się to metodą prób i błędów.

Zadanie 6 (1 punkt)

1. Dobierz wartość hiperparametru `max_features` :
 - użyj grid search z 5 foldami
 - wypróbuj wartości `[0.1, 0.2, 0.3, 0.4, 0.5]`
 - wybierz model o najwyższym AUROC (argument `scoring`)
2. Sprawdź, jaka była optymalna wartość `max_features`. Jest to atrybut wytrenowanego `GridSearchCV`.
3. Skomentuj wynik. Czy warto było poświęcić czas i zasoby na tę procedurę?

Uwaga:

- pamiętaj, żeby jako estymatora przekazanego do grid search'a użyć instancji Random Forest, która ma już ustawione `random_state=0` i `n_jobs`

```
In [ ]: from sklearn.model_selection import GridSearchCV

param_tuning_grid = { "max_features": [ .1, .2, .3, .4, .5 ] }
gs_clf = GridSearchCV(rf_clf, param_tuning_grid, scoring="roc_auc", verbose=2)
gs_clf.fit(X_train_balanced, y_train_balanced)

print()
print("Best results")
print("AUROC:\t\t", gs_clf.score(X_test, y_test))
print("Max features:\t", gs_clf.best_params_["max_features"])
```

```

Fitting 5 folds for each of 5 candidates, totalling 25 fits
[CV 1/5] END .....max_features=0.1;; score=0.998 total time=
5.1s
[CV 2/5] END .....max_features=0.1;; score=0.998 total time=
5.0s
[CV 3/5] END .....max_features=0.1;; score=0.999 total time=
5.2s
[CV 4/5] END .....max_features=0.1;; score=0.999 total time=
5.0s
[CV 5/5] END .....max_features=0.1;; score=0.998 total time=
4.8s
[CV 1/5] END .....max_features=0.2;; score=0.997 total time=
8.3s
[CV 2/5] END .....max_features=0.2;; score=0.998 total time=
8.9s
[CV 3/5] END .....max_features=0.2;; score=0.999 total time=
8.7s
[CV 4/5] END .....max_features=0.2;; score=0.999 total time=
8.5s
[CV 5/5] END .....max_features=0.2;; score=0.998 total time=
8.2s
[CV 1/5] END .....max_features=0.3;; score=0.997 total time=
11.7s
[CV 2/5] END .....max_features=0.3;; score=0.999 total time=
12.1s
[CV 3/5] END .....max_features=0.3;; score=0.999 total time=
12.0s
[CV 4/5] END .....max_features=0.3;; score=0.998 total time=
12.0s
[CV 5/5] END .....max_features=0.3;; score=0.999 total time=
11.8s
[CV 1/5] END .....max_features=0.4;; score=0.996 total time=
16.0s
[CV 2/5] END .....max_features=0.4;; score=0.999 total time=
15.1s
[CV 3/5] END .....max_features=0.4;; score=0.999 total time=
15.8s
[CV 4/5] END .....max_features=0.4;; score=0.998 total time=
15.3s
[CV 5/5] END .....max_features=0.4;; score=0.998 total time=
15.9s
[CV 1/5] END .....max_features=0.5;; score=0.996 total time=
19.0s
[CV 2/5] END .....max_features=0.5;; score=0.999 total time=
19.2s
[CV 3/5] END .....max_features=0.5;; score=0.999 total time=
19.4s
[CV 4/5] END .....max_features=0.5;; score=0.998 total time=
20.8s
[CV 5/5] END .....max_features=0.5;; score=0.998 total time=
20.1s

```

Best results

```

AUROC:          0.9122619804437986
Max features:    0.2

```

Komenatrz

Znowu efektywność naszego klasyfikatora wzrosła, osiągnęła ona wartość AUROC ~0.91. Jednakże operacja była kosztowna czasowo, dla mnie wynosiła ponad 5

minut. Dla tego konkretnego przypadku uważam, że było warto, natomiast tuningowany był tylko 1 hiperparametr w małej skali. Jeśli czas byłby znacząco większy, wtedy trzeba byłoby się zastanowić nad sensownością takiego kroku, biorąc pod uwagę fakt, że las losowy jest słabo podatny na zmianę hiperparametrów.

W praktycznych zastosowaniach data scientist wedle własnego uznania, doświadczenia, dostępnego czasu i zasobów wybiera, czy dostrajać hiperparametry i w jak szerokim zakresie. Dla Random Forest na szczęście często może nie być znaczącej potrzeby, i za to go lubimy :)

Random Forest - podsumowanie

1. Model oparty o uczenie zespołowe
2. Kluczowe elementy:
 - bagging: uczenie wielu klasyfikatorów na próbkach bootstrapowych
 - metoda losowej podprzestrzeni: losujemy podzbiór cech do każdego podziału drzewa
 - uśredniamy głosy klasyfikatorów
3. Dość odporny na overfitting, zmniejsza wariancję błędu dzięki uśrednianiu
4. Mało czuły na hiperparametry
5. Przeciętnie bardzo dobre wyniki, doskonały wybór domyślny przy wybieraniu algorytmu klasyfikacji

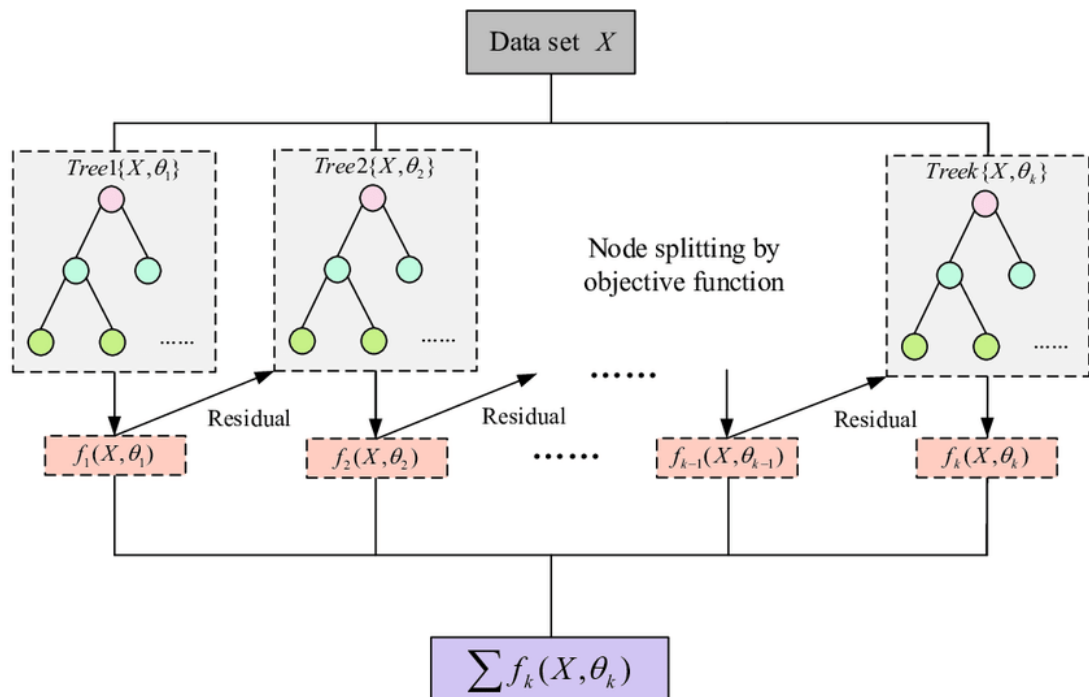
Boosting

Drugą bardzo ważną grupą algorytmów ensemblingu jest **boosting**, też oparty o drzewa decyzyjne. O ile Random Forest trenował wszystkie klasyfikatory bazowe równolegle i je uśredniał, o tyle boosting robi to sekwencyjnie. Drzewa te uczą się na całym zbiorze, nie na próbkach bootstrapowych. Idea jest następująca: trenujemy drzewo decyzyjne, radzi sobie przeciętnie i popełnia błędy na części przykładów treningowych. Dokładamy kolejne, ale znające błędy swojego poprzednika, dzięki czemu może to uwzględnić i je poprawić. W związku z tym "boostuje" się dzięki wiedzy od poprzednika. Dokładamy kolejne drzewa zgodnie z tą samą zasadą.

Jak uczyć się na błędach poprzednika? Jest to pewna **funkcja kosztu** (błędu), którą chcemy zminimalizować. Zakłada się jakąś jej konkretną postać, np. squared error dla regresji, albo logistic loss dla klasyfikacji. Później wykorzystuje się spadek wzdłuż gradientu (gradient descent), aby nauczyć się, w jakim kierunku powinny optymalizować kolejne drzewa, żeby zminimalizować błędy poprzednika. Jest to konkretnie **gradient boosting**, absolutnie najpopularniejsza forma boostingu, i jeden z najpopularniejszych i osiągających najlepsze wyniki algorytmów ML.

Tyle co do intuicji. Ogólny algorytm gradient boostingu jest trochę bardziej skomplikowany. Bardzo dobrze i krok po kroku tłumaczy go [ta seria filmów na YT](#). Szczególnie ważne implementacje gradient boostingu to **XGBoost (Extreme Gradient Boosting)** oraz **LightGBM (Light Gradient Boosting Machine)**. XGBoost był prawdziwym przełomem w ML, uzyskując doskonałe wyniki i bardzo dobrze się

skalując - był wykorzystany w CERNie do wykrywania cząstki Higgsa w zbiorze z pomiarów LHC mającym 10 milionów próbek. Jego implementacja jest dość złożona, ale dobrze tłumaczy ją [inna seria filmików na YT](#).



Obecnie najczęściej wykorzystuje się LightGBM. Został stworzony przez Microsoft na podstawie doświadczeń z XGBoostem. Został jeszcze bardziej ulepszony i przyspieszony, ale różnice są głównie implementacyjne. Różnice dobrze tłumaczy [ta prezentacja z konferencji PyData](#) oraz [prezentacja Microsoftu](#). Dla zainteresowanych - [praktyczne aspekty LightGBM](#).

Zadanie 7 (0.5 punktu)

1. Wytrenuj klasyfikator LightGBM (klasa `LGBMClassifier`). Przekaż `importance_type="gain"` - przyda nam się to za chwilę.
2. Sprawdź AUROC na zbiorze testowym.
3. Skomentuj wynik w odniesieniu do wcześniejszych algorytmów.

Pamiętaj o `random_state` i `n_jobs`.

```
In [ ]: from lightgbm import LGBMClassifier
lgbm_clf = LGBMClassifier(importance_type="gain", n_jobs=-1, random_state=42)
lgbm_clf = lgbm_clf.fit(X_train_balanced, y_train_balanced)
y_probabilities = lgbm_clf.predict_proba(X_test)

auroc = roc_auc_score(y_test, y_probabilities[:, 1])

print()
print("AUROC (LGBM classifier):", auroc)
```

```
[LightGBM] [Info] Number of positive: 8006, number of negative: 8006
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.003496 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 16012, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
```

AUROC (LGBM classifier): 0.9433748070111706

Komentarz

Wynik AUROC jest zdecydowanie najlepszy ze wszystkich wykorzystanych dotychczas klasyfikatorów. Warto zaznaczyć, że utworzenie otrzymanego modelu było błyskawiczne.

Boosting dzięki uczeniu na poprzednich drzewach redukuje nie tylko wariancję, ale też bias w błędzie, dzięki czemu może w wielu przypadkach osiągnąć lepsze rezultaty od lasu losowego. Do tego dzięki znakomitej implementacji LightGBM jest szybszy.

Boosting jest jednak o wiele bardziej czuły na hiperparametry niż Random Forest. W szczególności bardzo łatwo go przeuczyć, a większość hiperparametrów, których jest dużo, wiąże się z regularyzacją modelu. To, że teraz poszło nam lepiej z domyślnymi, jest rzadkim przypadkiem.

W związku z tym, że przestrzeń hiperparametrów jest duża, przeszukanie wszystkich kombinacji nie wchodzi w grę. Zamiast tego można wylosować zadaną liczbę zestawów hiperparametrów i tylko je sprawdzić - chociaż im więcej, tym lepsze wyniki powinniśmy dostać. Służy do tego `RandomizedSearchCV`. Co więcej, klasa ta potrafi próbkować rozkłady prawdopodobieństwa, a nie tylko sztywne listy wartości, co jest bardzo przydatne przy parametrach ciągłych.

Hiperparametry LightGBMa są dobrze opisane w oficjalnej dokumentacji: [wersja krótsza](#) i [wersja dłuższa](#). Jest ich dużo, więc nie będziemy ich tutaj omawiać. Jeżeli chodzi o ich dostrajanie w praktyce, to przydatny jest [oficjalny guide](#) oraz dyskusje na Kaggle.

Zadanie 8 (1.5 punktu)

1. Zaimplementuj random search dla LightGBMa (klasa `RandomizedSearchCV`):

- użyj tylu prób, na ile pozwalają twoje zasoby obliczeniowe, ale przynajmniej 30
- przeszukaj przestrzeń hiperparametrów:

```
param_grid = {
    "n_estimators": [400, 500, 600],
    "learning_rate": [0.05, 0.1, 0.2],
    "num_leaves": [31, 48, 64],
    "colsample_bytree": [0.8, 0.9, 1.0],
```

```
        "subsample": [0.8, 0.9, 1.0],
    }
```

2. Wypisz znalezione optymalne hiperparametry.
3. Wypisz raporty z klasyfikacji (funkcja `classification_report`), dla modelu LightGBM bez i z dostrajaniem hiperparametrów.
4. Skomentuj różnicę precyzji (precision) i czułości (recall) między modelami bez i z dostrajaniem hiperparametrów. Czy jest to pożądane zjawisko w tym przypadku?

Uwaga: pamiętaj o ustawieniu `importance_type`, `random_state=0` i `n_jobs`, oraz ewentualnie `verbose` dla śledzenia przebiegu

```
In [ ]: from sklearn.model_selection import RandomizedSearchCV

param_grid = {
    "n_estimators": [400, 500, 600],
    "learning_rate": [0.05, 0.1, 0.2],
    "num_leaves": [31, 48, 64],
    "colsample_bytree": [0.8, 0.9, 1.0],
    "subsample": [0.8, 0.9, 1.0],
}

randomized_search = RandomizedSearchCV(
    estimator=lgbm_clf,
    param_distributions=param_grid,
    n_iter=32,
    n_jobs=-1,
    random_state=0,
    verbose=3
)
randomized_search.fit(X_train_balanced, y_train_balanced)
```

Fitting 5 folds for each of 32 candidates, totalling 160 fits

[LightGBM] [Info] Number of positive: 6405, number of negative: 6404

[LightGBM] [Info] Number of positive: 6404, number of negative: 6405

[LightGBM] [Info] Number of positive: 6405, number of negative: 6405

[LightGBM] [Info] Number of positive: 6405, number of negative: 6404

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.013267 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 16065

[LightGBM] [Info] Number of positive: 6405, number of negative: 6405

[LightGBM] [Info] Number of positive: 6405, number of negative: 6405

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.014980 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 16065

[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63

[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.000156

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499961 -> initscore=-0.000156

[LightGBM] [Info] Start training from score -0.000156

[LightGBM] [Info] Start training from score 0.000156

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.003054 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 16065

[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Number of positive: 6404, number of negative: 6405

[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.002098 seconds.

You can set `force_row_wise=true` to remove the overhead.

And if memory is not enough, you can set `force_col_wise=true`.

[LightGBM] [Info] Total Bins 16065

[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.006229 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 16065

[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.002913 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 16065

[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499961 -> initscore=-0.000156

[LightGBM] [Info] Start training from score -0.000156

[illegible]

[illegible]

[illegible]

[illegible]


```

[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 2/5] END colsample_bytree=0.9, learning_rate=0.1, n_estimators=400, num_leaves=31, subsample=1.0;; score=0.995 total time= 11.8s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.052245 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.018961 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 1/5] END colsample_bytree=0.9, learning_rate=0.1, n_estimators=400, num_leaves=31, subsample=1.0;; score=0.985 total time= 11.9s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6405, number of negative: 6404
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.003508 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.000156
[LightGBM] [Info] Start training from score 0.000156
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 5/5] END colsample_bytree=0.9, learning_rate=0.1, n_estimators=400, nu
m_leaves=31, subsample=1.0;; score=0.993 total time= 14.0s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.040559 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 4/5] END colsample_bytree=0.9, learning_rate=0.2, n_estimators=500, num_leaves=64, subsample=0.8;; score=0.996 total time= 13.6s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6404, number of negative: 6405
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.025543 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499961 -> initscore=-0.000156
[LightGBM] [Info] Start training from score -0.000156
[CV 5/5] END colsample_bytree=0.9, learning_rate=0.2, n_estimators=500, num_leaves=64, subsample=0.8;; score=0.995 total time= 13.8s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.033571 seconds.
```

You can set `force_col_wise=true` to remove the overhead.

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[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[CV 2/5] END colsample_bytree=0.8, learning_rate=0.1, n_estimators=500, nu
m_leaves=31, subsample=0.9;; score=0.994 total time= 13.9s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.013911 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[CV 1/5] END colsample_bytree=0.8, learning_rate=0.1, n_estimators=500, nu
m_leaves=31, subsample=0.9;; score=0.986 total time= 14.3s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.051147 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 3/5] END colsample_bytree=0.8, learning_rate=0.1, n_estimators=500, nu
m_leaves=31, subsample=0.9;; score=0.996 total time= 13.9s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6405, number of negative: 6404
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.007479 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.00
0156
[LightGBM] [Info] Start training from score 0.000156
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 3/5] END colsample_bytree=0.8, learning_rate=0.2, n_estimators=600, nu
m_leaves=48, subsample=0.8;; score=0.996 total time= 13.5s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6405, number of negative: 6404
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.008281 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of
used features: 63
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.00
0156
[LightGBM] [Info] Start training from score 0.000156
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 1/5] END colsample_bytree=0.8, learning_rate=0.2, n_estimators=500, nu
m_leaves=64, subsample=1.0;; score=0.986 total time= 15.9s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6405, number of negative: 6404
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.002481 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of
used features: 63
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.00
0156
[LightGBM] [Info] Start training from score 0.000156
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 4/5] END colsample_bytree=0.8, learning_rate=0.2, n_estimators=500, nu
m_leaves=64, subsample=1.0;; score=0.996 total time= 14.4s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Info] Number of positive: 6404, number of negative: 6405
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.018850 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of data points in the train set: 12809, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499961 -> initscore=-0.0
00156
[LightGBM] [Info] Start training from score -0.000156
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 5/5] END colsample_bytree=0.8, learning_rate=0.2, n_estimators=500, nu
m_leaves=64, subsample=1.0;; score=0.994 total time= 14.2s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
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[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
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[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 5/5] END colsample_bytree=1.0, learning_rate=0.2, n_estimators=600, nu
m_leaves=31, subsample=0.8;; score=0.994 total time= 13.1s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.047413 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 5/5] END colsample_bytree=1.0, learning_rate=0.2, n_estimators=400, num_leaves=64, subsample=0.9;; score=0.993 total time= 13.4s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Info] Number of positive: 6404, number of negative: 6405
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.029732 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499961 -> initscore=-0.000156
[LightGBM] [Info] Start training from score -0.000156
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 4/5] END colsample_bytree=0.9, learning_rate=0.2, n_estimators=600, num_leaves=48, subsample=0.9;; score=0.997 total time= 14.5s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6404, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.004151 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 3/5] END colsample_bytree=0.9, learning_rate=0.2, n_estimators=600, num_leaves=48, subsample=0.8;; score=0.996 total time= 16.0s[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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m_leaves=31, subsample=0.8;; score=0.997 total time= 10.3s
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.004219 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.003071 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[CV 2/5] END colsample_bytree=1.0, learning_rate=0.05, n_estimators=600, n
um_leaves=64, subsample=1.0;; score=0.995 total time= 33.4s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001963 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[CV 3/5] END colsample_bytree=1.0, learning_rate=0.05, n_estimators=600, n
um_leaves=64, subsample=1.0;; score=0.995 total time= 32.5s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6404
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.052947 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.00
0156
[LightGBM] [Info] Start training from score 0.000156
[CV 4/5] END colsample_bytree=1.0, learning_rate=0.05, n_estimators=600, n
um_leaves=64, subsample=1.0;; score=0.995 total time= 32.8s
[LightGBM] [Info] Number of positive: 6404, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.004470 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499961 -> initscore=-0.0
00156
[LightGBM] [Info] Start training from score -0.000156
[CV 5/5] END colsample_bytree=1.0, learning_rate=0.05, n_estimators=600, n
um_leaves=64, subsample=1.0;; score=0.994 total time= 32.9s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.006305 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 4/5] END colsample_bytree=0.9, learning_rate=0.1, n_estimators=600, num_leaves=48, subsample=0.9;; score=0.996 total time= 26.1s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.003294 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[CV 1/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=400, num_leaves=64, subsample=1.0;; score=0.984 total time= 21.4s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.003222 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[CV 1/5] END colsample_bytree=1.0, learning_rate=0.1, n_estimators=500, num_leaves=31, subsample=1.0;; score=0.985 total time= 13.5s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.003853 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63


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[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[CV 2/5] END colsample_bytree=1.0, learning_rate=0.1, n_estimators=500, num_leaves=31, subsample=1.0;; score=0.993 total time= 13.5s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6404
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.002494 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.000156
[LightGBM] [Info] Start training from score 0.000156
[CV 3/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=400, num_leaves=64, subsample=1.0;; score=0.995 total time= 21.2s
[LightGBM] [Info] Number of positive: 6404, number of negative: 6405
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.019880 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499961 -> initscore=-0.000156
[LightGBM] [Info] Start training from score -0.000156
[CV 3/5] END colsample_bytree=1.0, learning_rate=0.1, n_estimators=500, num_leaves=31, subsample=1.0;; score=0.997 total time= 13.5s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.002465 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[CV 2/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=400, num_leaves=64, subsample=1.0;; score=0.993 total time= 26.0s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.003545 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[CV 5/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=400, num_leaves=64, subsample=1.0;; score=0.993 total time= 21.6s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.018869 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 3/5] END colsample_bytree=0.9, learning_rate=0.2, n_estimators=500, nu
m_leaves=31, subsample=0.9;; score=0.997 total time= 11.5s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 5/5] END colsample_bytree=1.0, learning_rate=0.1, n_estimators=500, nu
m_leaves=31, subsample=1.0;; score=0.993 total time= 14.2s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.026036 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.022400 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 2/5] END colsample_bytree=0.9, learning_rate=0.2, n_estimators=500, num_leaves=31, subsample=0.9;; score=0.994 total time= 13.4s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6405, number of negative: 6404
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.032160 seconds.
You can set `force_col_wise=true` to remove the overhead.[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

[LightGBM] [Info] Total Bins 16065
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.000156[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

[LightGBM] [Info] Start training from score 0.000156
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 5/5] END colsample_bytree=0.9, learning_rate=0.2, n_estimators=500, num_leaves=31, subsample=0.9;; score=0.994 total time= 11.4s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.003579 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[CV 1/5] END colsample_bytree=0.9, learning_rate=0.05, n_estimators=500, num_leaves=31, subsample=0.8;; score=0.981 total time= 14.5s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.011324 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[CV 3/5] END colsample_bytree=0.9, learning_rate=0.05, n_estimators=500, num_leaves=31, subsample=0.8;; score=0.994 total time= 14.4s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.008584 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[CV 2/5] END colsample_bytree=0.9, learning_rate=0.05, n_estimators=500, num_leaves=31, subsample=0.8;; score=0.993 total time= 17.1s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6404
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.011211 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.000156
[LightGBM] [Info] Start training from score 0.000156
[CV 5/5] END colsample_bytree=0.9, learning_rate=0.05, n_estimators=500, num_leaves=31, subsample=0.8;; score=0.993 total time= 14.2s
[CV 4/5] END colsample_bytree=0.9, learning_rate=0.05, n_estimators=500, n

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 5/5] END colsample_bytree=0.9, learning_rate=0.1, n_estimators=500, num_leaves=64, subsample=0.8;; score=0.994 total time= 21.8s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.002560 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[CV 1/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=400, num_leaves=48, subsample=1.0;; score=0.981 total time= 20.9s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6404
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.023019 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.000156
[LightGBM] [Info] Start training from score 0.000156
[CV 4/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=400, num_leaves=48, subsample=1.0;; score=0.994 total time= 17.3s
[LightGBM] [Info] Number of positive: 6404, number of negative: 6405
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.016201 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499961 -> initscore=-0.000156
[LightGBM] [Info] Start training from score -0.000156
[CV 5/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=400, num_leaves=48, subsample=1.0;; score=0.993 total time= 17.2s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.006633 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065

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[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[CV 1/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=600, n
um_leaves=48, subsample=0.9;; score=0.984 total time= 25.0s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.013803 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[CV 2/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=600, n
um_leaves=48, subsample=0.9;; score=0.994 total time= 24.7s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.048976 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.00
0000
[CV 1/5] END colsample_bytree=1.0, learning_rate=0.05, n_estimators=400, n
um_leaves=64, subsample=0.8;; score=0.983 total time= 22.1s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6404
[CV 4/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=600, n
um_leaves=48, subsample=0.9;; score=0.996 total time= 25.2s
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.095811 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of
used features: 63
[LightGBM] [Info] Number of positive: 6404, number of negative: 6405
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500039 -> initscore=0.00
0156
[LightGBM] [Info] Start training from score 0.000156
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.037548 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12809, number of
used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499961 -> initscore=-0.0
00156
[LightGBM] [Info] Start training from score -0.000156
[CV 5/5] END colsample_bytree=0.8, learning_rate=0.05, n_estimators=600, n
um_leaves=48, subsample=0.9;; score=0.994 total time= 25.5s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.002952 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of
used features: 63

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[illegible]

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[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 2/5] END colsample_bytree=1.0, learning_rate=0.2, n_estimators=600, num_leaves=31, subsample=1.0;; score=0.993 total time= 12.2s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 6404, number of negative: 6405
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.012302 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of data points in the train set: 12809, number of used features: 63
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499961 -> initscore=-0.000156
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Start training from score -0.000156
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 3/5] END colsample_bytree=1.0, learning_rate=0.2, n_estimators=600, num_leaves=31, subsample=1.0;; score=0.997 total time= 12.1s
[LightGBM] [Info] Number of positive: 6405, number of negative: 6405
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.002545 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 12810, number of

```


[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

used features: 63

```
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

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[illegible]

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[illegible]

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 5/5] END colsample_bytree=0.8, learning_rate=0.1, n_estimators=500, num_leaves=64, subsample=1.0;; score=0.994 total time= 13.3s
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[CV 4/5] END colsample_bytree=0.8, learning_rate=0.1, n_estimators=500, num_leaves=64, subsample=1.0;; score=0.995 total time= 14.0s
[LightGBM] [Info] Number of positive: 8006, number of negative: 8006
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.002153 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 16065
[LightGBM] [Info] Number of data points in the train set: 16012, number of used features: 63
[LightGBM] [Info] [binary:BoostFromScore]: pavgq=0.500000 -> initscore=0.00
```

[illegible]

```
In [ ]: lgbm_clf_tuned = randomized_search.best_estimator_
print("Best parameters")
for param_name in randomized_search.best_params_:
    print(f"{param_name}: {randomized_search.best_params_[param_name]}")
```

Best parameters
subsample: 0.8
num_leaves: 31
n_estimators: 400
learning_rate: 0.2
colsample_bytree: 0.9

```
In [ ]: from sklearn.metrics import classification_report

print("Without tuning")
print(classification_report(y_test, lgbm_clf.predict(X_test)))

print("With tuning")
print(classification_report(y_test, lgbm_clf_tuned.predict(X_test)))
```

Without tuning

	precision	recall	f1-score	support
0	0.98	0.98	0.98	2002
1	0.60	0.60	0.60	99
accuracy			0.96	2101
macro avg	0.79	0.79	0.79	2101
weighted avg	0.96	0.96	0.96	2101

With tuning

	precision	recall	f1-score	support
0	0.98	0.99	0.98	2002
1	0.76	0.52	0.61	99
accuracy			0.97	2101
macro avg	0.87	0.75	0.80	2101
weighted avg	0.97	0.97	0.97	2101

Komentarz

Dla klasy **0** wartości precyzji i czułości są praktycznie tożsame. Natomiast w przypadku klasy **1** (przedsiębiorstwo zbankrutuje po 3 latach działalności), wartości się już istotnie od siebie różnią, dla tuningu hiperparametrów precyzja wzrosła o 16 p.p., a czułość się zmniejszyła o 8 p.p. Uważam, że precyzja w tym wypadku jest lepszym wskaźnikiem, ponieważ chcemy się dowiedzieć o dokładności detekcji potencjalnych bankrutów.

Boosting - podsumowanie

1. Model oparty o uczenie zespołowe
2. Kolejne modele są dodawane sekwencyjnie i uczą się na błędach poprzedników
3. Nauka typowo jest oparta o minimalizację funkcji kosztu (błędu), z użyciem spadku wzdłuż gradientu
4. Wiodący model klasyfikacji dla danych tabelarycznych, z 2 głównymi implementacjami: XGBoost i LightGBM
5. Liczne hiperparametry, wymagające odpowiednich metod dostrajania

Wyjaśnialna AI

W ostatnich latach zaczęto zwracać coraz większą uwagę na wpływ sztucznej inteligencji na społeczeństwo, a na niektórych czołowych konferencjach ML nawet obowiązkowa jest sekcja "Social impact" w artykułach naukowych. Typowo im lepszy model, tym bardziej złożony, a najpopularniejsze modele boostingu są z natury skomplikowane. Kiedy mają podejmować krytyczne decyzje, to musimy wiedzieć, czemu predykcja jest taka, a nie inna. Jest to poddziedzina uczenia maszynowego - **wyjaśnialna AI (explainable AI, XAI)**.

Taka informacja jest cenna, bo dzięki temu lepiej wiemy, co robi model. Jest to ważne z kilku powodów:

1. Wymogi prawne - wdrażanie algorytmów w ekonomii, prawie etc. ma coraz częściej konkretne wymagania prawne co do wyjaśnialności predykcji
2. Dodatkowa wiedza dla użytkowników - często dodatkowe obserwacje co do próbek są ciekawe same w sobie i dają wiedzę użytkownikowi (często posiadającemu specjalistyczną wiedzę z dziedziny), czasem nawet bardziej niż sam model predykcyjny
3. Analiza modelu - dodatkowa wiedza o wewnętrznym działaniu algorytmu pozwala go lepiej zrozumieć i ulepszyć wyniki, np. przez lepszy preprocessing danych

W szczególności można ją podzielić na **globalną** oraz **lokalną interpretowalność (global / local interpretability)**. Ta pierwsza próbuje wyjaśnić, czemu ogólnie model działa tak, jak działa. Analizuje strukturę modelu oraz trendy w jego predykcjach, aby podsumować w prostszy sposób jego tok myślenia. Interpretowalność lokalna z kolei dotyczy predykcji dla konkretnych próbek - czemu dla danego przykładu model podejmuje dla niego taką, a nie inną decyzję o klasyfikacji.

W szczególności podstawowym sposobem interpretowalności jest **ważność cech (feature importance)**. Wyznacza ona, jak ważne są poszczególne cechy:

- w wariancie globalnym, jak mocno model opiera się na poszczególnych cechach
- w wariancie lokalnym, jak mocno konkretne wartości cech wpłynęły na predykcję, i w jaki sposób

Teraz będzie nas interesować globalna ważność cech. Dla modeli drzewiastych definiuje się ją bardzo prosto. Każdy podział w drzewie decyzyjnym wykorzystuje jakąś cechę, i redukuje z pomocą podziału funkcję kosztu (np. entropię) o określoną ilość. Dla drzewa decyzyjnego ważność to sumaryczna redukcja entropii, jaką udało się uzyskać za pomocą danej cechy. Dla lasów losowych i boostingu sumujemy te wartości dla wszystkich drzew. Alternatywnie można też użyć liczby splitów, w jakiej została użyta dana cecha, ale jest to mniej standardowe.

Warto zauważyć, że taka ważność cech jest **względna**:

- nie mówimy, jak bardzo ogólnie ważna jest jakaś cecha, tylko jak bardzo przydatna była dla naszego modelu w celu jego wytrenowania
- ważność cech można tylko porównywać ze sobą, np. jedna jest 2 razy ważniejsza od drugiej; nie ma ogólnych progów ważności

Ze względu na powyższe, ważności cech normalizuje się często do zakresu [0, 1] dla łatwiejszego porównywania.

Zadanie 9 (0.5 punktu)

1. Wybierz 5 najważniejszych cech dla drzewa decyzyjnego. Przedstaw wyniki na poziomym wykresie słupkowym. Użyj czytelnych nazw cech ze zmiennej `feature_names`.
2. Powtórz powyższe dla lasu losowego, oraz dla boostingu (tutaj znormalizuj wyniki - patrz uwaga niżej). Wybierz te hiperparametry, które dały wcześniej najlepsze wyniki.
3. Skomentuj, czy wybrane cechy twoim zdaniem mają sens jako najważniejsze cechy.

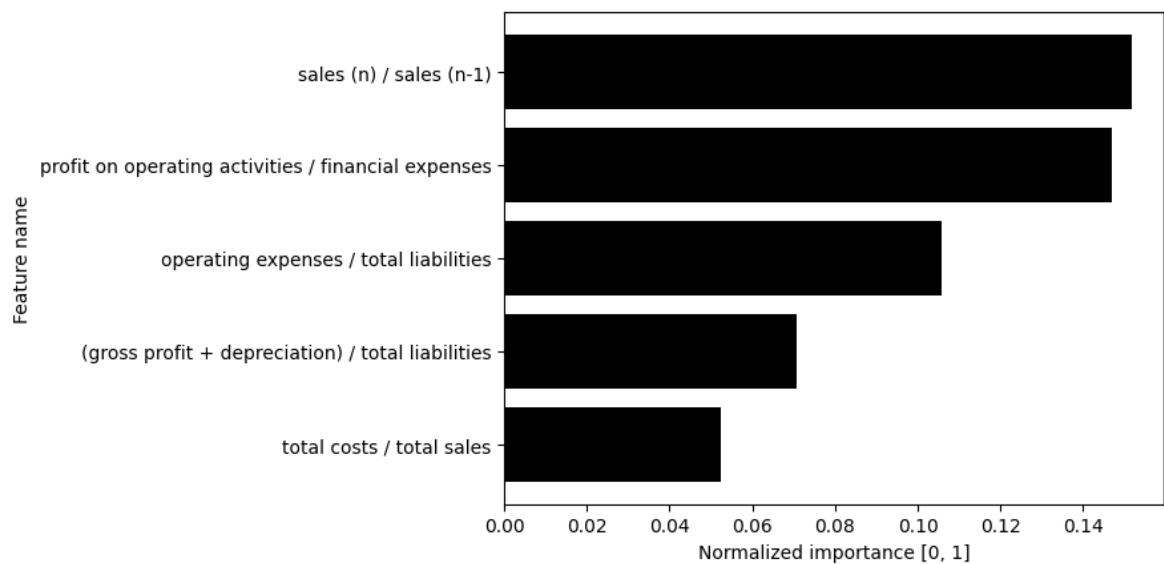
Uwaga: Scikit-learn normalizuje ważności do zakresu [0, 1], natomiast LightGBM nie. Musisz to znormalizować samodzielnie, dzieląc przez sumę.

```
In [ ]: import matplotlib.pyplot as plt

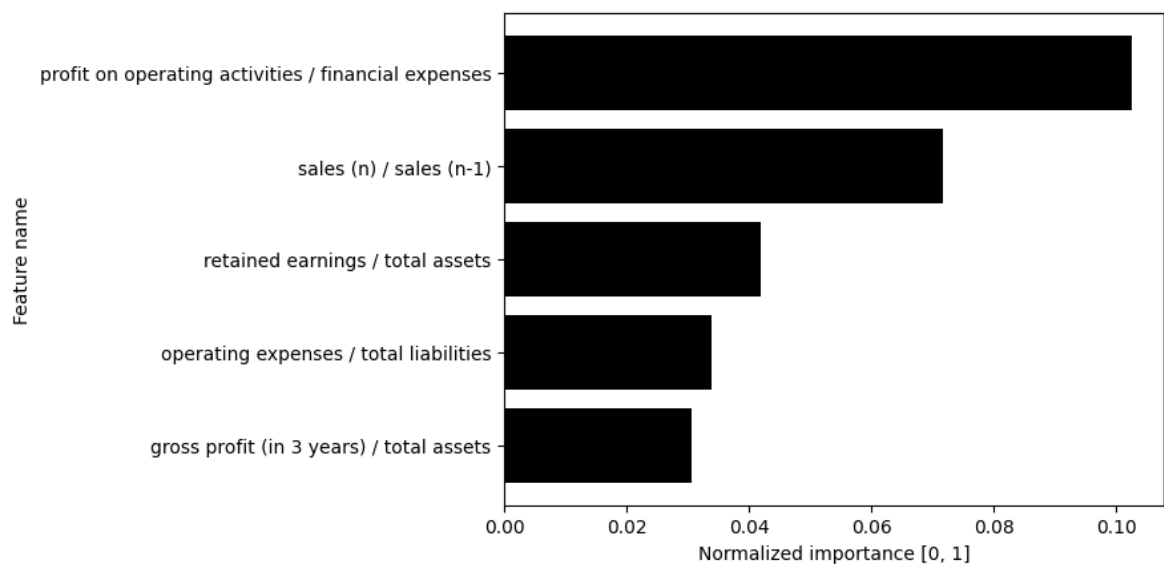
def render_barh(feature_importances, feature_names):
    features = sorted(zip(feature_importances, feature_names), r
    feature_importances = [f[0] for f in features]
    feature_names = [f[1] for f in features]

    _, ax = plt.subplots()
    ax.set_ylabel("Feature name")
    ax.set_xlabel("Normalized importance [0, 1]")
    ax.invert_yaxis()
    ax.barh(feature_names[:5], feature_importances[:5], color="black")
    plt.show()
```

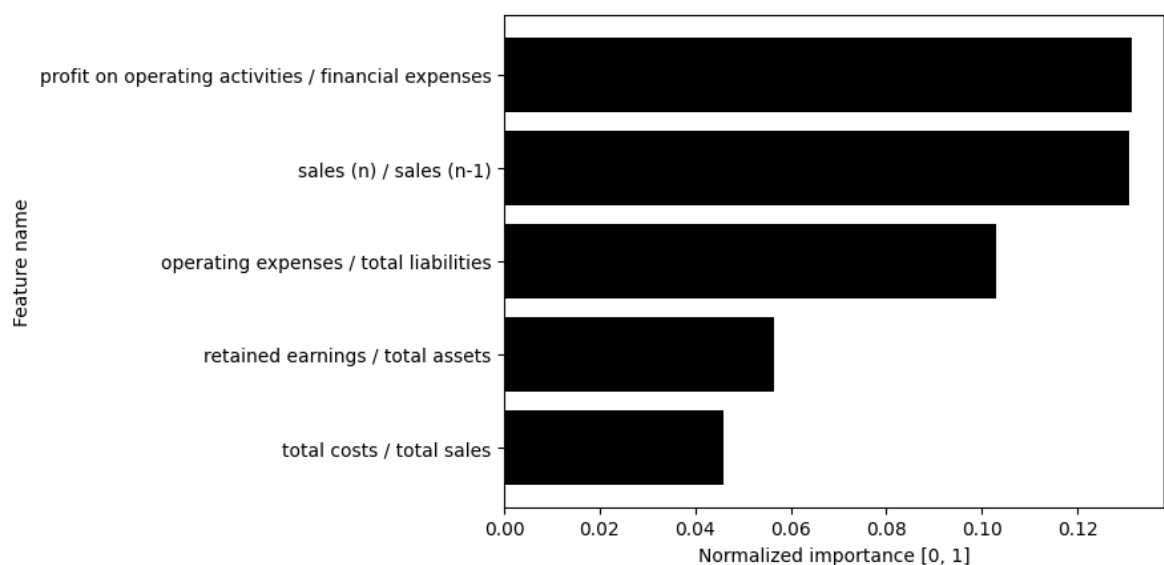
```
In [ ]: render_barh(dt_clf.feature_importances_, feature_names)
```



```
In [ ]: render_barh(rf_clf.feature_importances_, feature_names)
```



```
In [ ]: feature_importances_sum = lgbm_clf_tuned.feature_importances_.sum()
render_barh(lgbm_clf_tuned.feature_importances_ / feature_importances_sum
```



Komentarz

Większość cech się powtarza na wszystkich 3 wykresach. Powyższe cechy, które klasyfikatory wybrały za najważniejsze są jak najbardziej poprawne według mnie, mogą służyć za czynnik odpowiedzialny za bankructwo przedsiębiorstwa.

Dla zainteresowanych

Najpopularniejszym podejściem do interpretowalności lokalnych jest **SHAP (SHapley Additive exPlanations)**, metoda oparta o kooperatywną teorię gier. Traktuje się cechy modelu jak zbiór graczy, podzielonych na dwie drużyny (koalicje): jedna chce zaklasyfikować próbkę jako negatywną, a druga jako pozytywną. O ostatecznej decyzji decyduje model, który wykorzystuje te wartości cech. Powstaje pytanie - w jakim stopniu wartości cech przyczyniły się do wyniku swojej drużyny? Można to obliczyć jako wartości Shapleya (Shapley values), które dla modeli ML oblicza algorytm SHAP. Ma on bardzo znaczące, udowodnione matematycznie zalety, a dodatkowo posiada wyjątkowo efektywną implementację dla modeli drzewiastych oraz dobre wizualizacje.

Bardzo intuicyjnie, na prostym przykładzie, SHAPa wyjaśnia [pierwsza część tego artykułu](#). Dobrze i dość szczegółowo SHAPa wyjaśnia jego autor [w tym filmie](#).

Wyjaśnialna AI - podsumowanie

1. Problem zrozumienia, jak wnioskuje model i czemu podejmuje dane decyzje
2. Ważne zarówno z perspektywy data scientist'a, jak i użytkowników systemu
3. Można wyjaśniać model lokalnie (konkretne predykcje) lub globalnie (wpływ poszczególnych cech)

Zadanie dla chętnych

Dokonaj selekcji cech, usuwając 20% najślabszych cech. Może się tu przydać klasa `SelectPercentile`. Czy Random Forest i LightGBM (bez dostrajania hiperparametrów, dla uproszczenia) wytrenowane bez najślabszych cech dają lepszy wynik (AUROC lub innej metryki)?

Wykorzystaj po 1 algorytmie z 3 grup algorytmów selekcji cech:

1. Filter methods - mierzymy ważność każdej cechy niezależnie, za pomocą pewnej miary (typowo ze statystyki lub teorii informacji), a potem odrzucamy (filtrujemy) te o najniższej ważności. Są to np. `chi2` i `mutual_info_classif` z pakietu `sklearn.feature_selection`.
2. Embedded methods - klasyfikator sam zwraca ważność cech, jest jego wbudowaną cechą (stąd nazwa). Jest to w szczególności właściwość wszystkich zespołowych klasyfikatorów drzewiastych. Mają po wytrenowaniu atrybut `feature_importances_`.
3. Wrapper methods - algorytmy wykorzystujące w środku używany model (stąd nazwa), mierzące ważność cech za pomocą ich wpływu na jakość klasyfikatora. Jest to np. recursive feature elimination (klasa `RFE`). W tym algorytmie

trenujemy klasyfikator na wszystkich cechach, wyrzucamy najłabszą, trenujemy znowu i tak dalej.

Typowo metody filter są najszybsze, ale dają najłabszy wynik, natomiast metody wrapper są najwolniejsze i dają najlepszy wynik. Metody embedded są gdzieś pośrodku.

Dla zainteresowanych, inne znane i bardzo dobre algorytmy:

- Relief (filter method) oraz warianty, szczególnie ReliefF, SURF i MultiSURF (biblioteka `ReBATE`): [Wikipedia](#)), [artykuł "Benchmarking Relief-Based Feature Selection Methods"](#)
- Boruta (wrapper method), stworzony na Uniwersytecie Warszawskim, łączący Random Forest oraz testy statystyczne (biblioteka `boruta_py`): [link 1](#), [link 2](#)

In []: