



Advanced Machine Learning



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What will We Learn Today?

1. What is imbalance data
2. Handling imbalance data
3. Dimensionality reduction
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Profile

Professional

- Senior Data Analyst – Kompas (2021 – Present)
- Data Scientist – Rukita (2020 – 2021)
- Research Assistant Analyst – Ensterna (2017 – 2019)

Educational Background

- Nuclear Engineering – Universitas Gadjah Mada

Connect with me

 <https://dataimpact.medium.com/>

 <https://www.linkedin.com/in/ariprabowo/>

 <https://github.com/densaiko>



Ari Sulistiyo Prabowo



Imbalance data

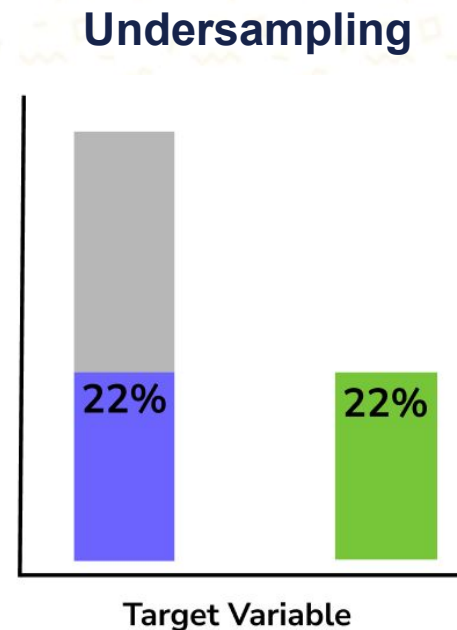
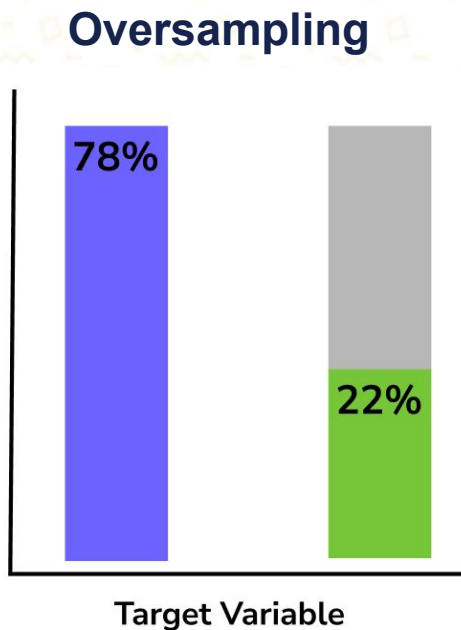
target variable yang memiliki jumlah data yang tidak seimbang 50:50



Imbalance data

Terdapat dua hal dalam membuat data menjadi balance:

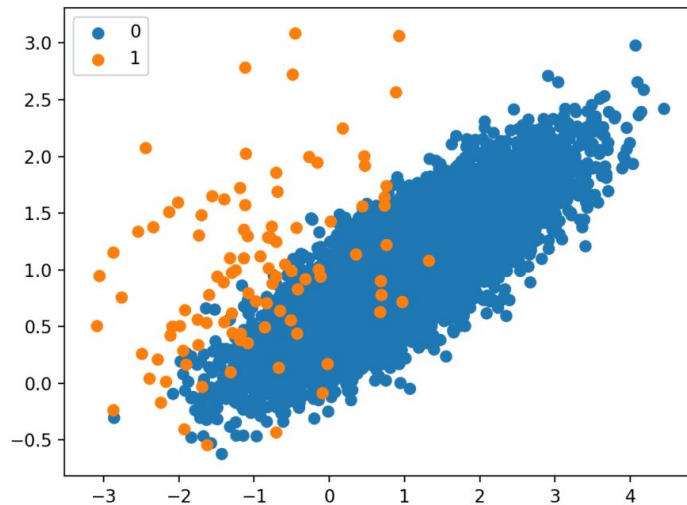
1. **Oversampling:** menambahkan data pada target variable yang sedikit
2. **Undersampling:** mengurangi data pada target variable yang banyak



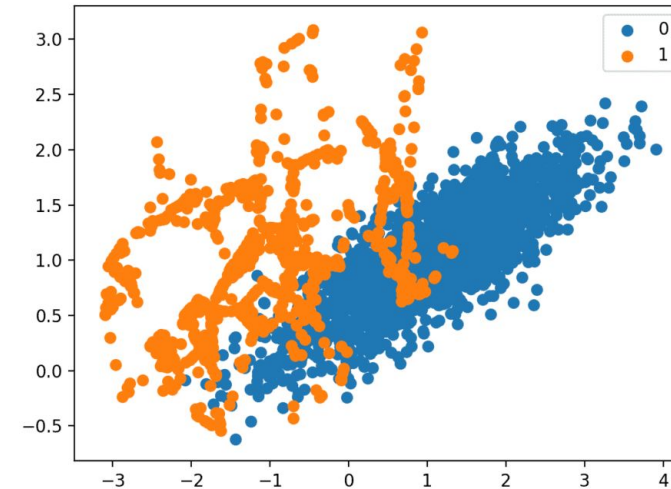


Imbalance data (*Smote*)

Dalam imbalance data, terutama oversampling, dilakukan penambahan data sintesis dengan menggunakan library **SMOTE**



Before Oversampling



After Oversampling



Imbalance data (Smote)

```
from imblearn.over_sampling import SMOTE #oversampling
```



```
# oversampling  
sm = SMOTE(random_state=25, sampling_strategy=1) #sampling strategy 0.x to 1  
  
# fit the sampling  
X_train, y_train = sm.fit_sample(X_train, y_train)  
  
y_train.value_counts()
```



```
Before smoting Counter({2: 5440, 1: 4703, 3: 2736, 0: 1638})  
After smoting Counter({1: 5440, 3: 5440, 2: 5440, 0: 5440})
```



Dimensionality Reduction

Mengurangi dimensi suatu dataset



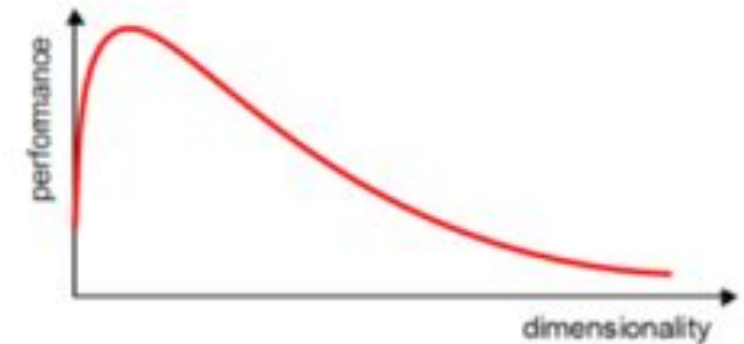
Dimensionality Reduction

Manfaat melakukan pengurangan dimensi:

- Mengurangi misleading data yang membuat akurasi model meningkat
- Mengurangi dimensi, mengurangi komputasi
- Mengurangi feature yang redundant

Terdapat **dua teknik** di dalam dimensionality reduction

- Feature selection
- Feature extraction





Hands on *(binary classification)*

Objective

X company would like to assess the employee to get a promotion. There are some criteria whether this employee can be promoted or not. Therefore, HR needs help from data scientist to create a machine learning model.

Target Variable

is_promoted

- 1 (promoted)
- 0 (not promoted)





Feature Selection

Feature selection adalah proses memilih subset dari fitur-fitur relevan dari seluruh fitur yang ada di dataset. Beberapa hal keuntungan feature selection:

- Mengurangi waktu komputasi
- Mengurangi data yang tidak relevan
- Meningkatkan akurasi

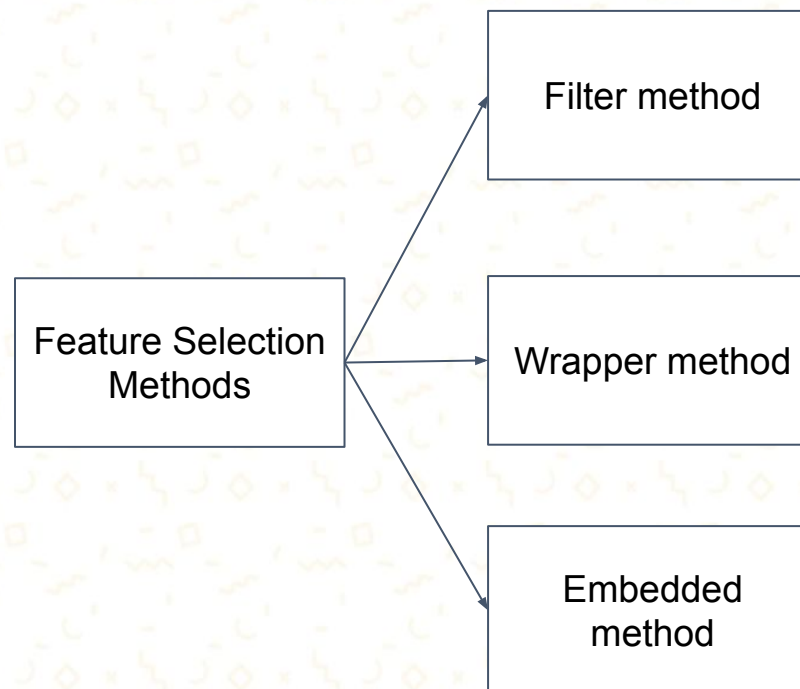
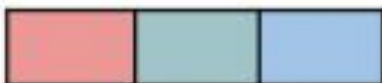
All Features



Feature Selection



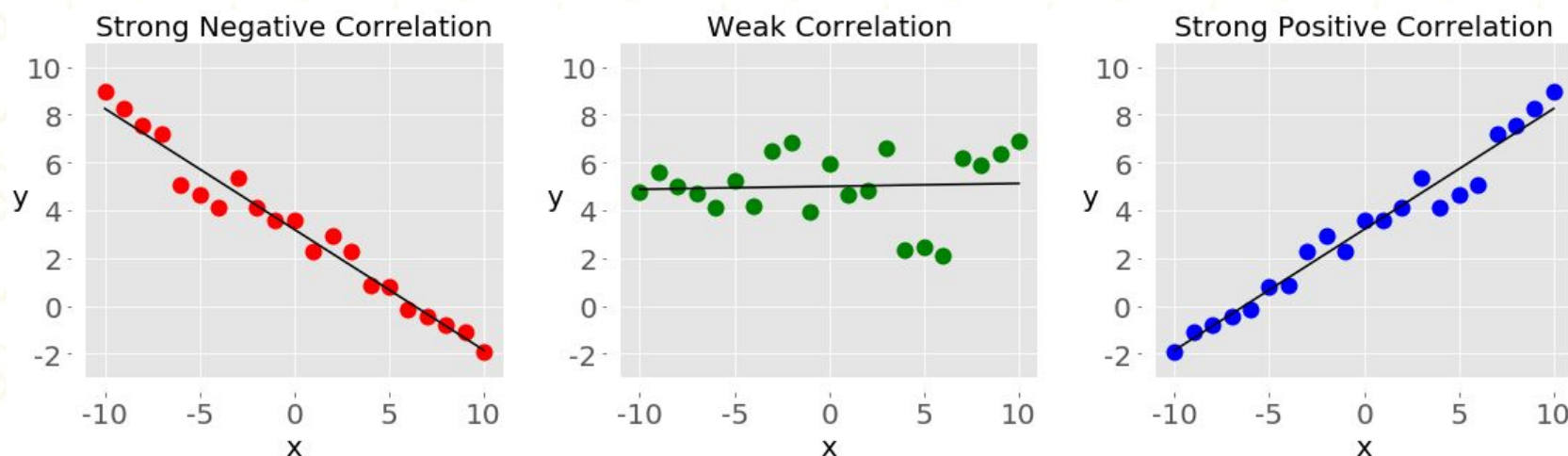
Final Features





Filter Method

Metode filter digunakan dengan melihat fitur-fitur yang memiliki korelasi yang tinggi.



Pada filter metode ini kita menggunakan metode statistik yaitu ANOVA yang digunakan untuk menganalisis variance untuk menentukan jika **rata-rata** dari lebih dari dua populasi adalah **sama**



Filter Method

```
from sklearn.feature_selection import SelectKBest, f_classif
```

```
filter = SelectKBest(f_classif, k=5)  
filter.fit(X_train, y_train)
```

```
X_train_new = filter.transform(X_train)  
X_test_new = filter.transform(X_test)
```

```
print("Before feature selection", X_train.shape)  
print("After feature selection", X_train_new.shape)
```

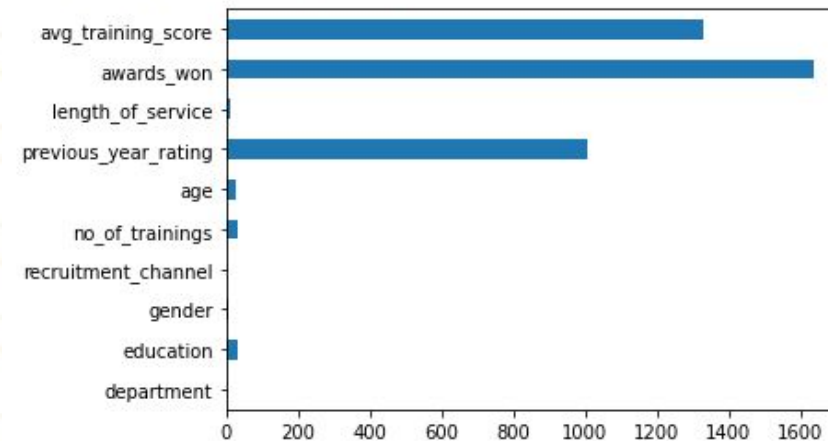
```
Before feature selection (37104, 10)  
After feature selection (37104, 5)
```

Features = 5

Selected Features = avg_training_score, awards_won, previous_year_rating, education, no_of_trainings

Baseline ML (Logistic Regression)	91.79%
Logistic Regression + Anova	92.03%

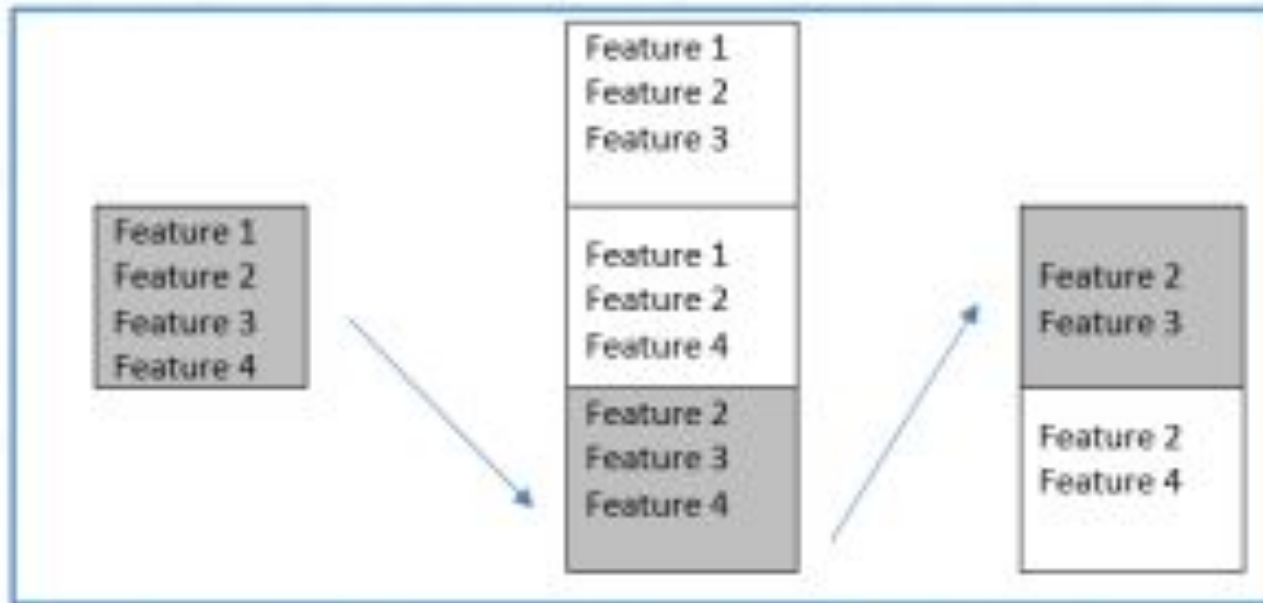
Score of features [1.58485364e-01 3.26275563e+01 6.63837086e+00 1.47834343e+00
3.00369928e+01 2.54122347e+01 1.00475625e+03 1.02120870e+01
1.63478931e+03 1.33002169e+03]





Wrapper Method

Metode wrapper digunakan untuk menemukan kombinasi variable yang terbaik. Salah satu metode wrapper adalah RFE (Recursive Feature Elimination (RFE))





Wrapper Method

```
from sklearn.feature_selection import RFE

wrapper = RFE(clf, n_features_to_select=5)
wrapper.fit(X_train, y_train)

X_train_wrapper = wrapper.transform(X_train)
X_test_wrapper = wrapper.transform(X_test)
```

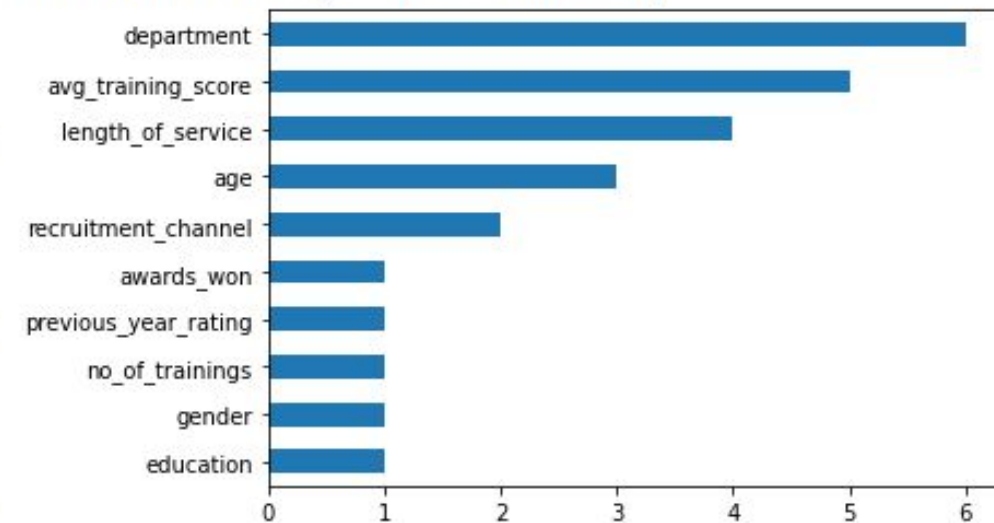
Features = 5

Selected Features = avg_training_score, awards_worn, previous_year_rating, education, no_of_trainings

Baseline ML (Logistic Regression)	91.79%
Logistic Regression + Anova	92.03%
Logistic Regression + RFE	91.83%

Before feature selection (37104, 10)
After feature selection (37104, 5)

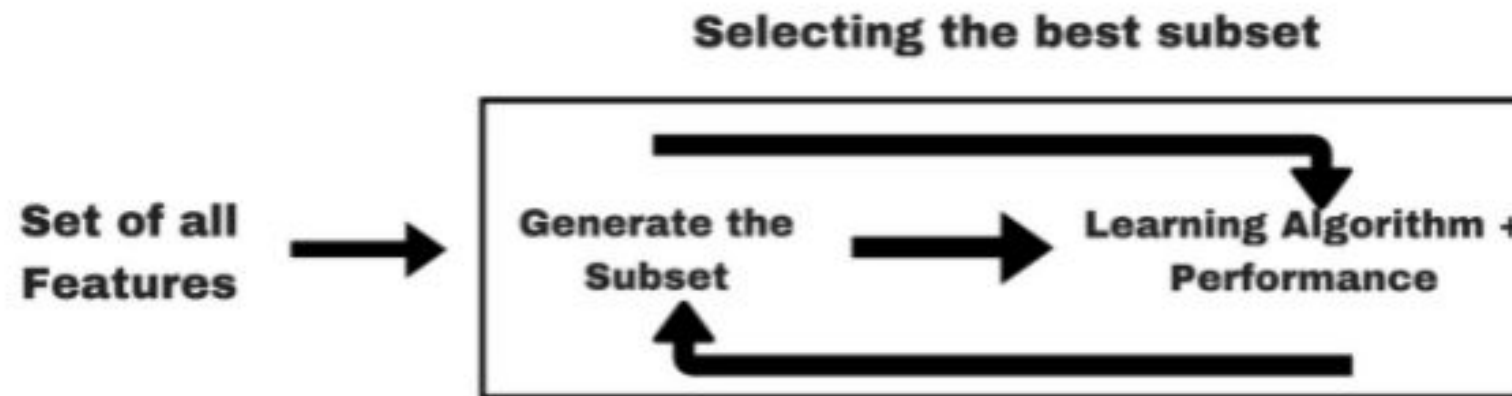
Score of features [6 1 1 2 1 3 1 4 1 5]





Embedded Method

Metode embedded ini digunakan untuk memilih fitur-fitur mana aja yang digunakan dari hasil performa algoritma machine learning model





Embedded Method

```
from sklearn.feature_selection import SelectFromModel

clf = LogisticRegression()
clf_feature = SelectFromModel(clf)

clf_feature.fit(X_train, y_train)

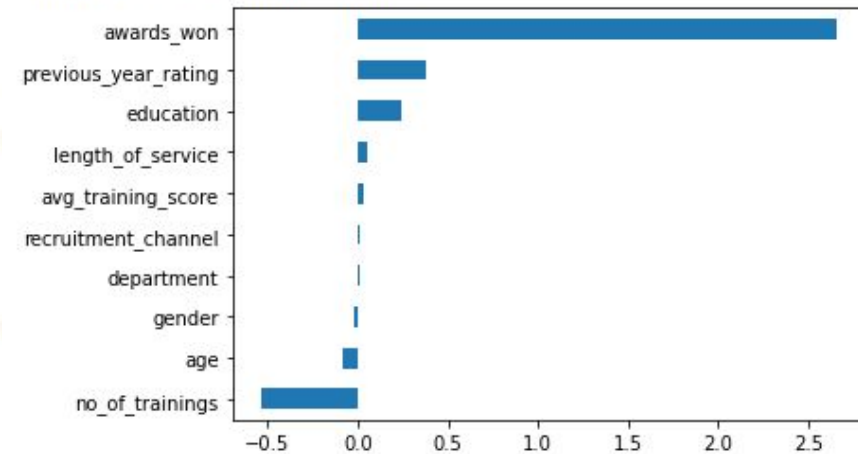
X_train_importance = clf_feature.transform(X_train)
X_test_importance = clf_feature.transform(X_test)
```

Features = 2

Selected Features = awards_worn, previous_year_rating

Baseline ML (Logistic Regression)	91.79%
Logistic Regression + Anova	92.03%
Logistic Regression + RFE	91.83%
Logistic Regression + Feature Importance	91.67%

Coef [0.01008519 0.2411234 -0.0189336 0.01141018 -0.53517601 -0.08410499
0.37662892 0.05672754 2.66393455 0.02762389]
Treshold 0.4025748276559864

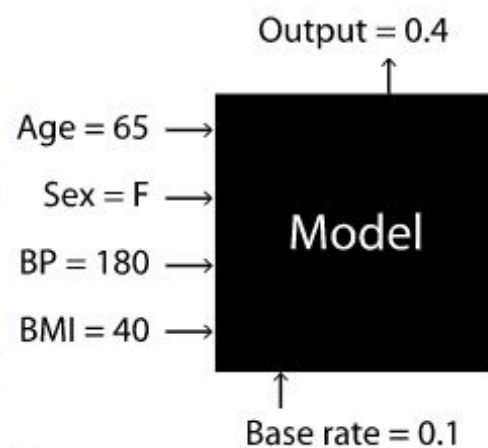




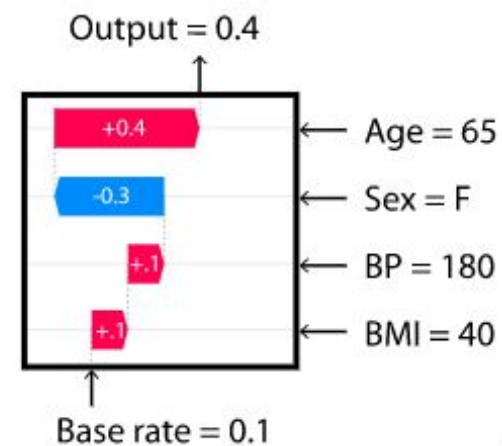
Explainable AI (BONUS)



SHAP



Explanation





Explainable AI (BONUS)

SHAP (SHapley Additive exPlanations) is a game theoretic approach **to explain the output of any machine learning model**. It connects optimal credit allocation with local explanations using the classic Shapley values from game theory and their related extensions



Features **pushing the prediction higher** are shown in **red**, those **pushing the prediction lower** are in **blue**

**Thank
YOU**

