

# Airline Passenger Satisfaction

Explainable Artificial Intelligence (XAI) techniques

Group PA2\_DS3\_GC: Athos Freitas up202108792 | Félix Martins up202108837 | Luís Du up202105385

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## Quality of the explanations

Functionally-grounded metric to evaluate explanations generated by post-hoc XAI techniques

**01**

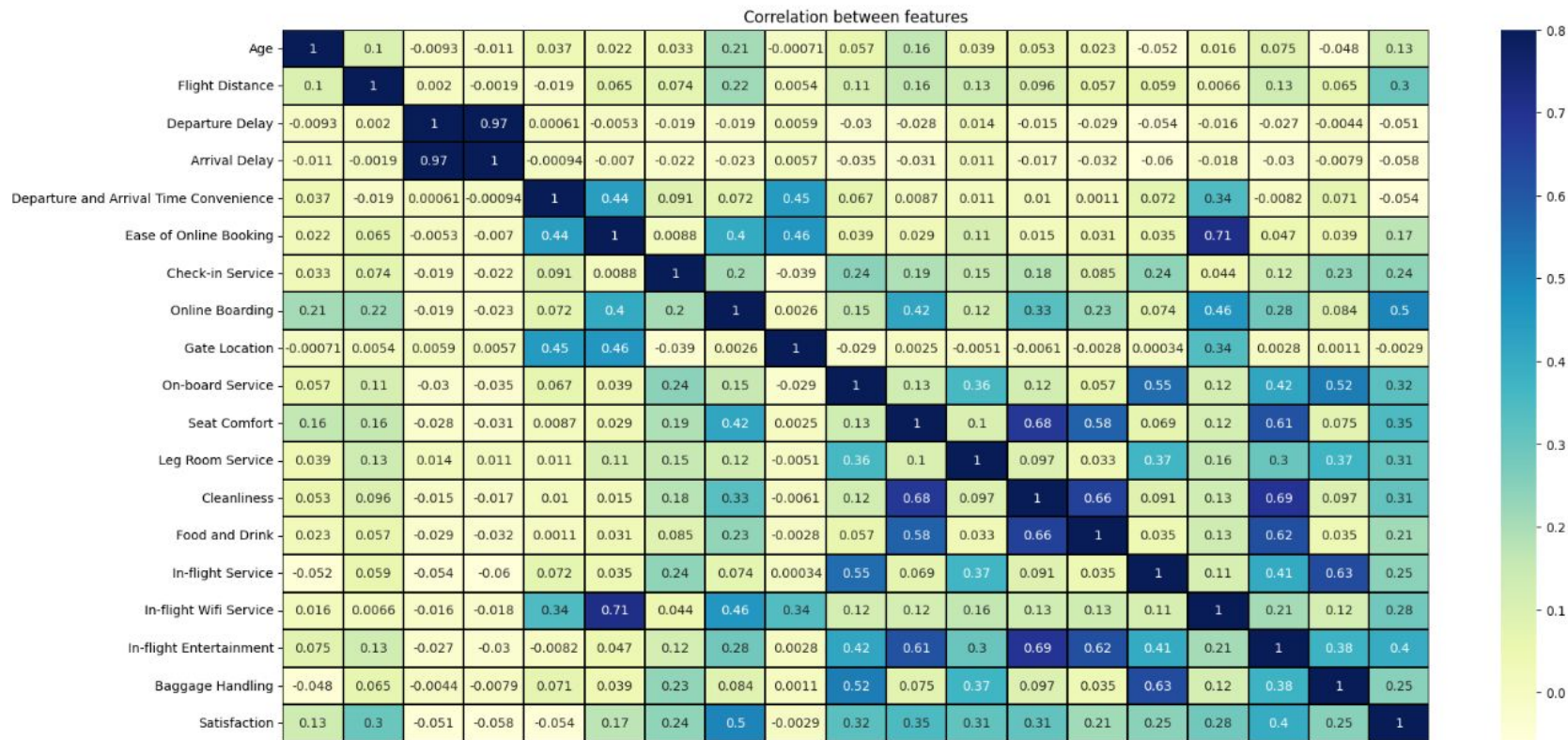
# **Pre-modelling**

# About this dataset

This dataset contains an airline passenger satisfaction survey.

<b>Dimensionality</b>	24 Columns and 129880 Rows.
<b>Target class</b>	<b>Neutral or Dissatisfied:</b> 56.6% <b>Satisfied:</b> 43.4%
<b>Features</b>	<b>Passenger data</b> - gender, age <b>Travel information</b> - business/personal, economy/business <b>Flight information</b> - flight distance, arrival/departure delay <b>Satisfaction levels (1-5)</b> related to specific travel aspects (service quality)
<b>Missing values</b>	0.013% Missing values; Dropped 393 rows with missing values.
<b>Duplicate rows</b>	There are no duplicate rows in the dataset.

# Correlation matrix



# Preprocessing

## One-Hot encode categorical features

Transform categorical values (*Gender, Customer Type, Type of Travel, Class*) into binary columns

## Standardize numerical features

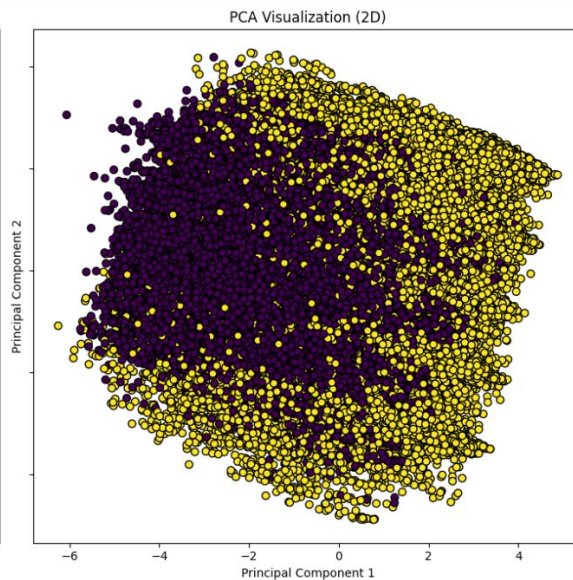
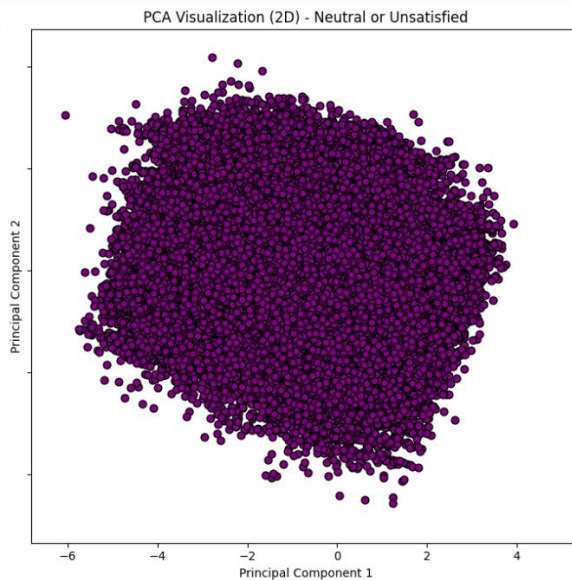
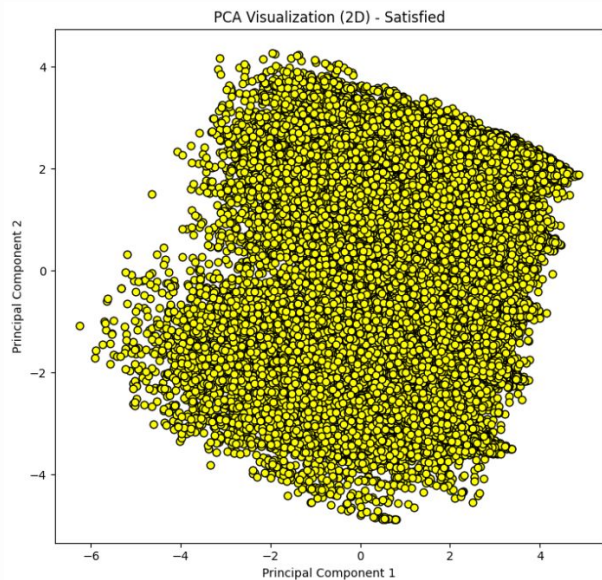
Transform numerical values to have a mean of 0 and a standard deviation of 1 - (same scale)

## Remove highly correlated features

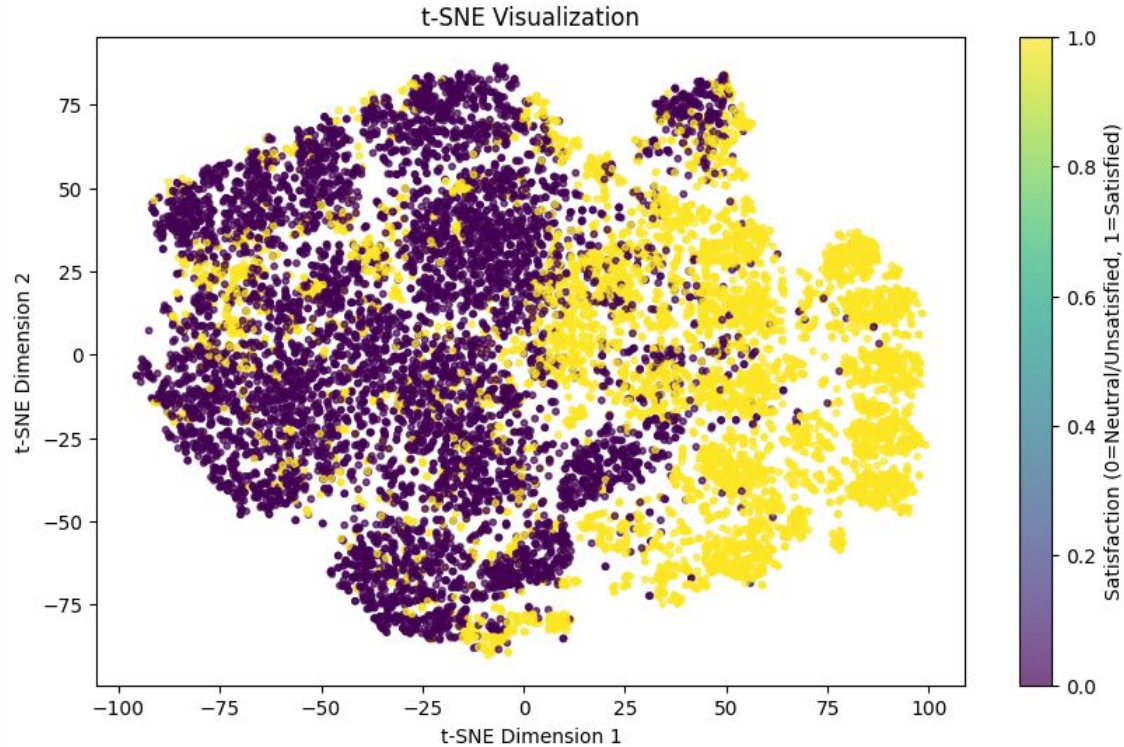
Remove features with high correlation ( $> 0.8$ ), keeping only the one with the highest variance.

```
preprocessor = ColumnTransformer(  
    transformers = [  
        ('cat', OneHotEncoder(drop='first'), categorical_columns),  
        ('num', StandardScaler(), numerical_columns),  
        ('remove_corr', RemoveHighlyCorrelated(), numerical_columns)  
    ]  
)
```

# Principal Component Analysis (PCA)



# t-distributed Stochastic Neighbor Embedding

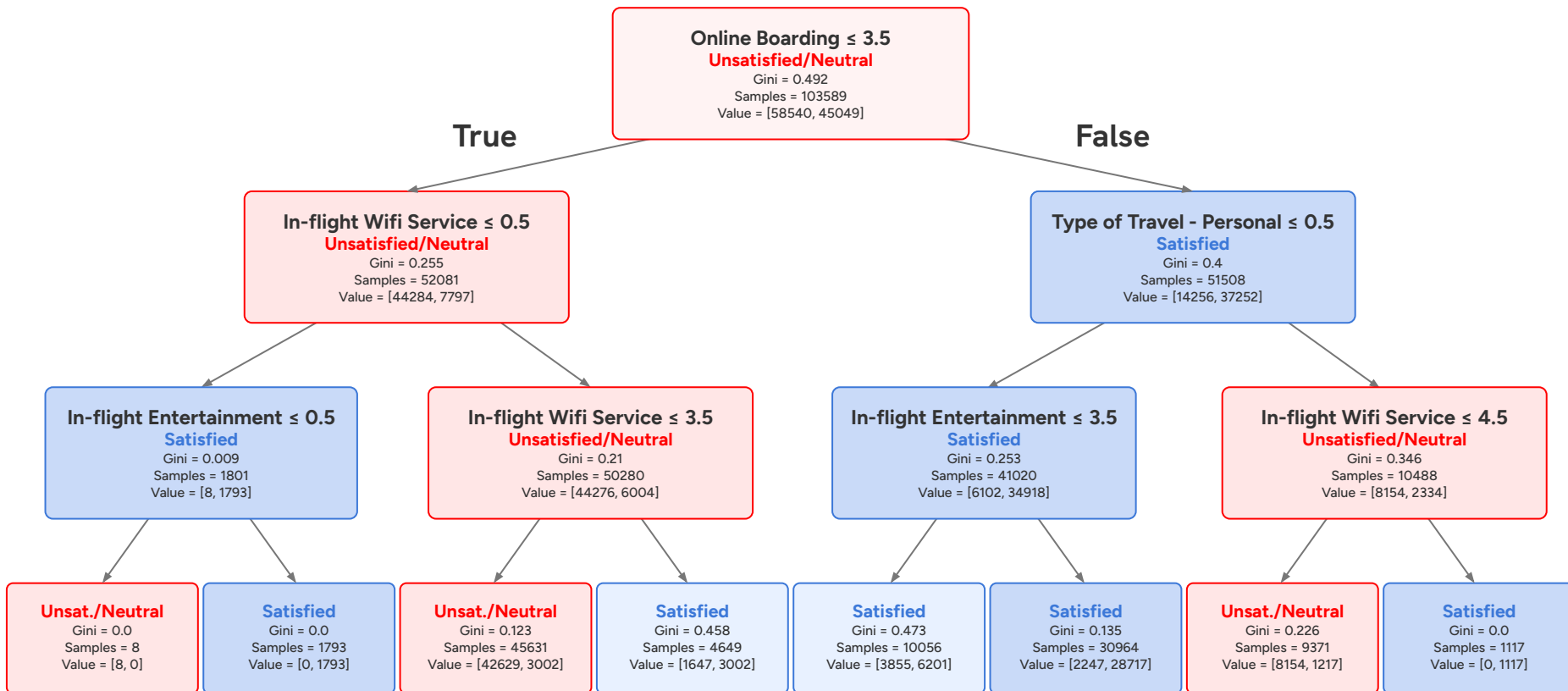




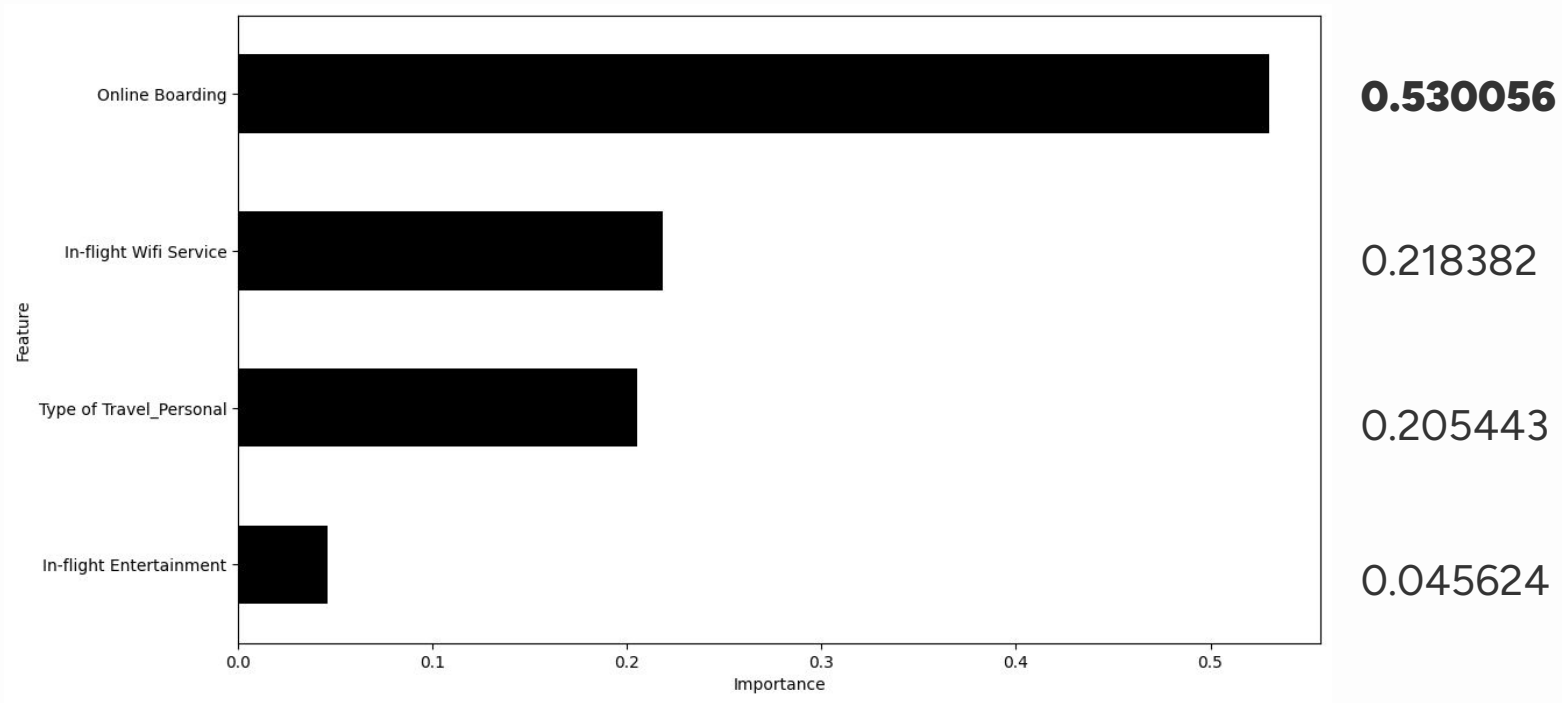
**02**

# **In-modelling**

# Glass-box model - *Decision Tree*



# Feature importance



**03**

# **Post-modelling**

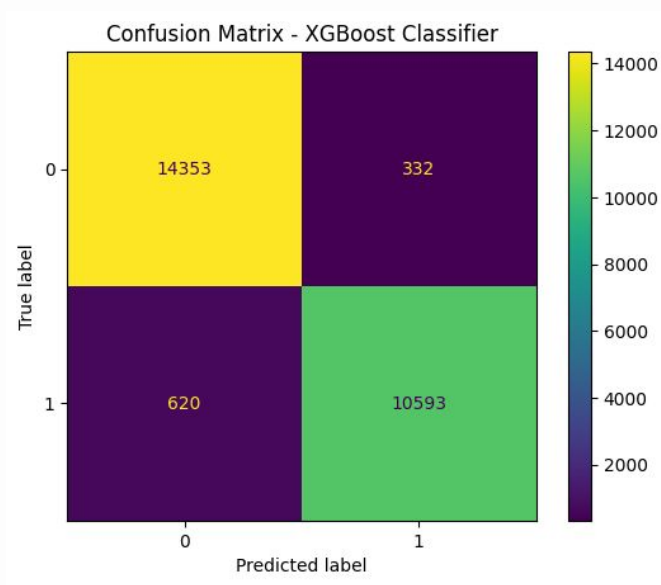
# Black-box model - *XGBoost*

**Accuracy: 96.3%**

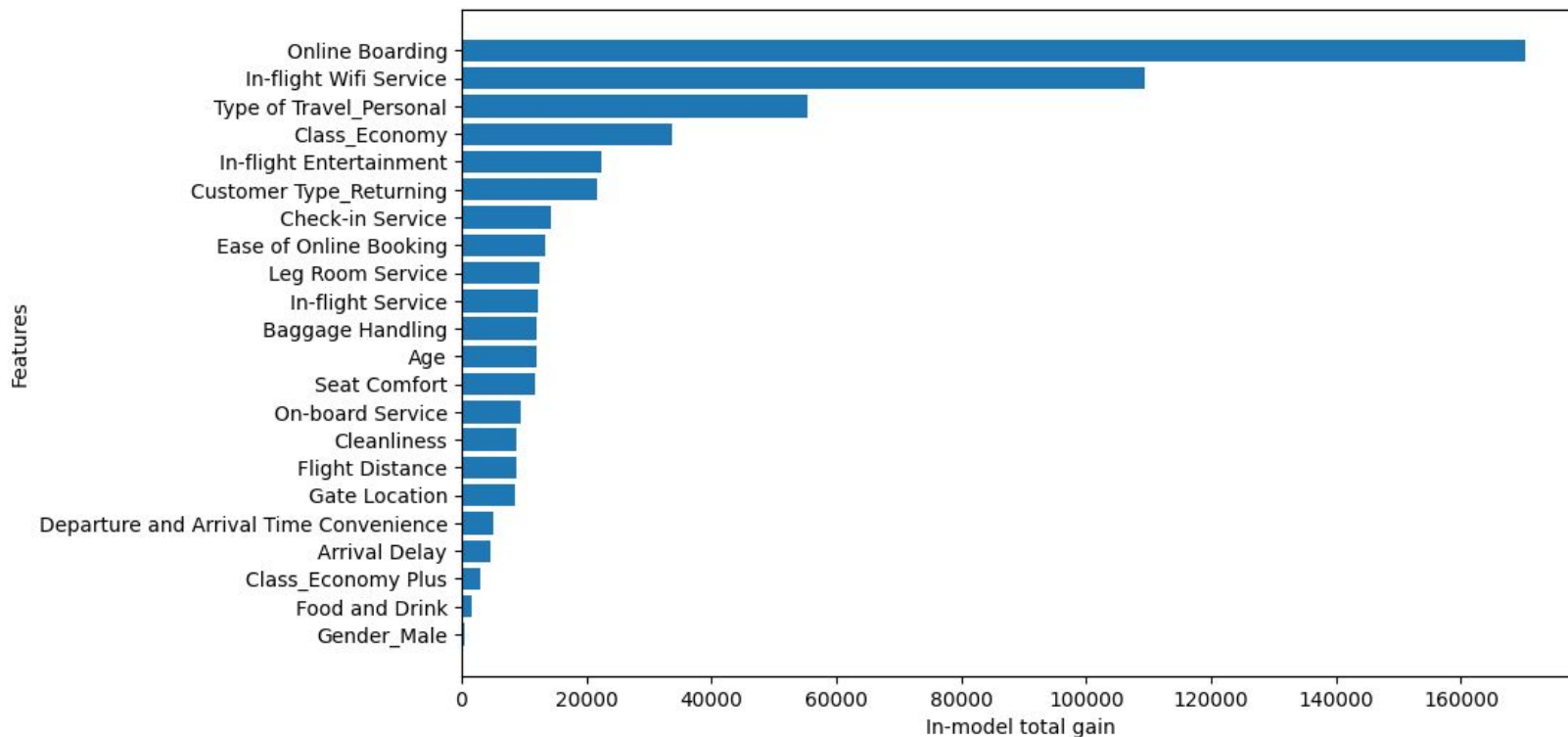
- Tree-based model
- Evaluation metric: Logarithmic loss function

**Fine-tuned accuracy: 96.5%**

- Evaluation metric: Logarithmic loss function
- Estimators : 200
- Max depth: 7



# XGBoost In-model Feature Importance



# Surrogate Model - Decision Tree

## Small Decision Tree to approximate Black Box model

Decision Tree with maximum depth 3

## Evaluation: Agreement Rate

Accuracy with black box predictions as ground truth and surrogate model predictions as predicted values

```
surrogate_model = DecisionTreeClassifier(max_depth=3)
surrogate_pipeline = Pipeline(steps = [
    ('preprocessor', preprocessor),
    ('classifier', surrogate_model),
])
y_train_surrogate = black_box.predict(X_train)
surrogate_pipeline.fit(X_train, y_train_surrogate)
agreement_rate = accuracy_score(y_true=y_pred, y_pred=y_pred_surrogate)
```

# Surrogate Model - Decision Tree

The surrogate decision tree obtained was exactly the same as the Glass-Box model trained on the data for In-modelling explanations.

Results:

- **Agreement rate**, evaluates fidelity: 89.6%
- **Accuracy**, in the actual data: 88.5%

## Black-Box and post-hoc surrogate Glass-Box

- Best possible accuracy
- Explanations: less precise, can lead to confusion

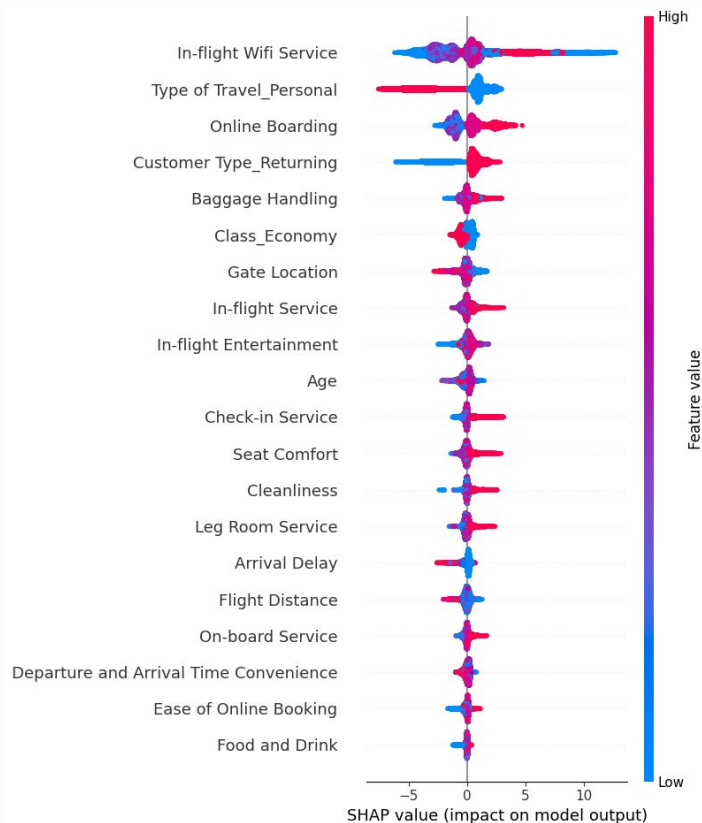
## In-modelling Glass-Box

- Worse accuracy
- Precise explanations
- Better when explanations are valued above everything else

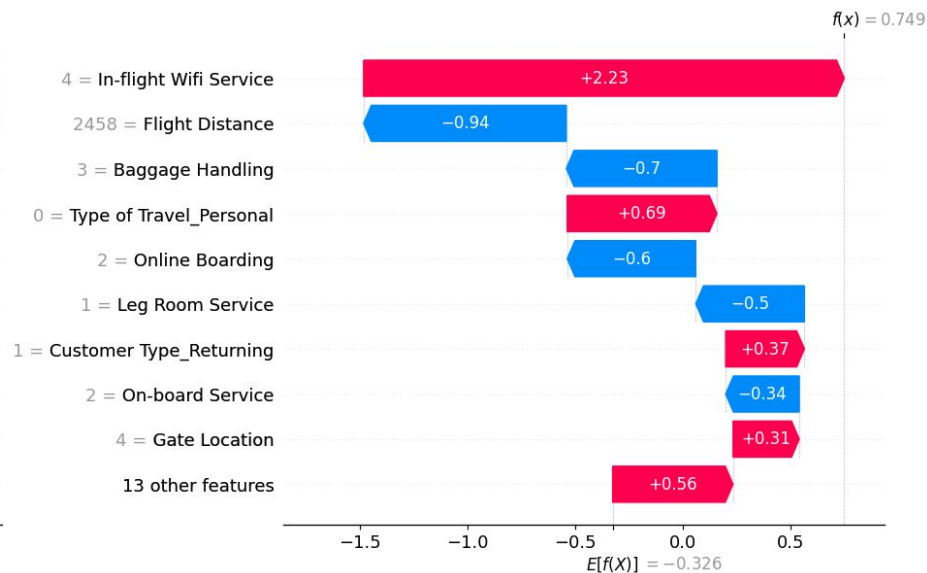
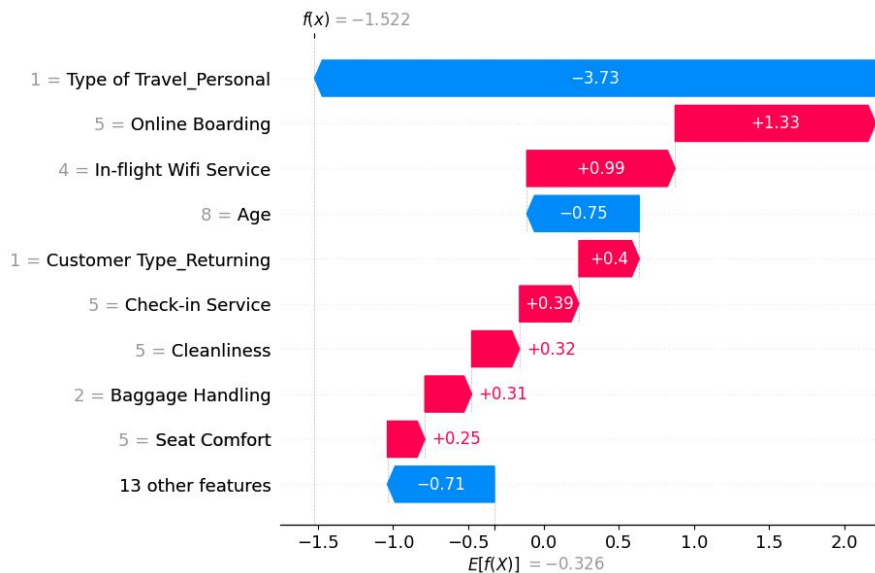


# SHAP - Global explanation

- Type of travel - Personal
  - Personal travelling impacts negatively (towards Dissatisfied or Neutral)
  - Business travelling impacts positively (towards satisfied)
- Customer type - Returning
  - Returning customer impacts positively
  - First impact negatively

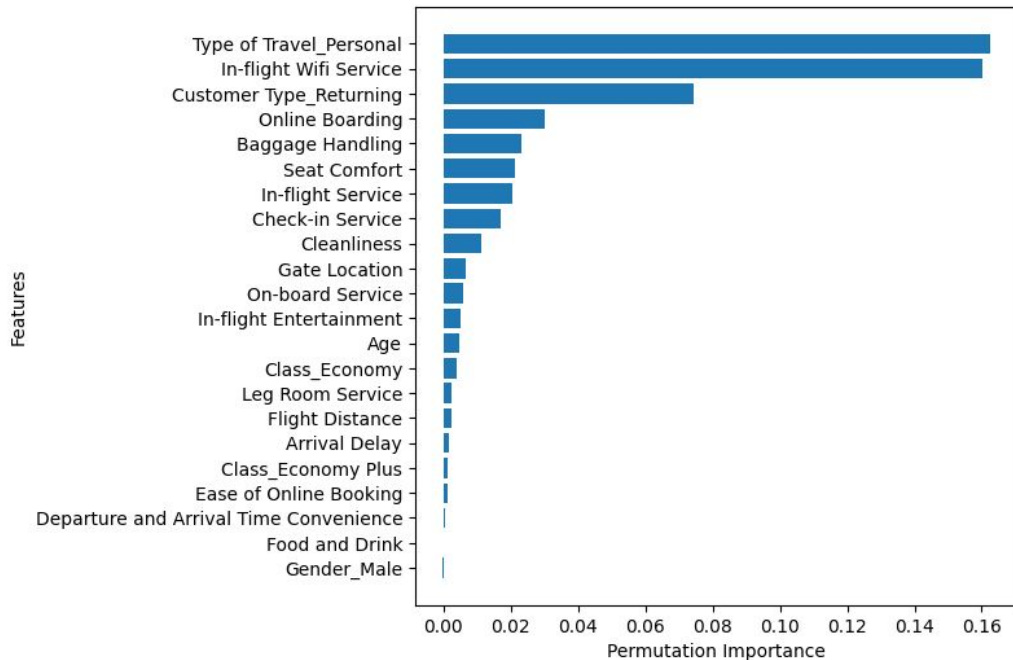


# SHAP - Local explanation

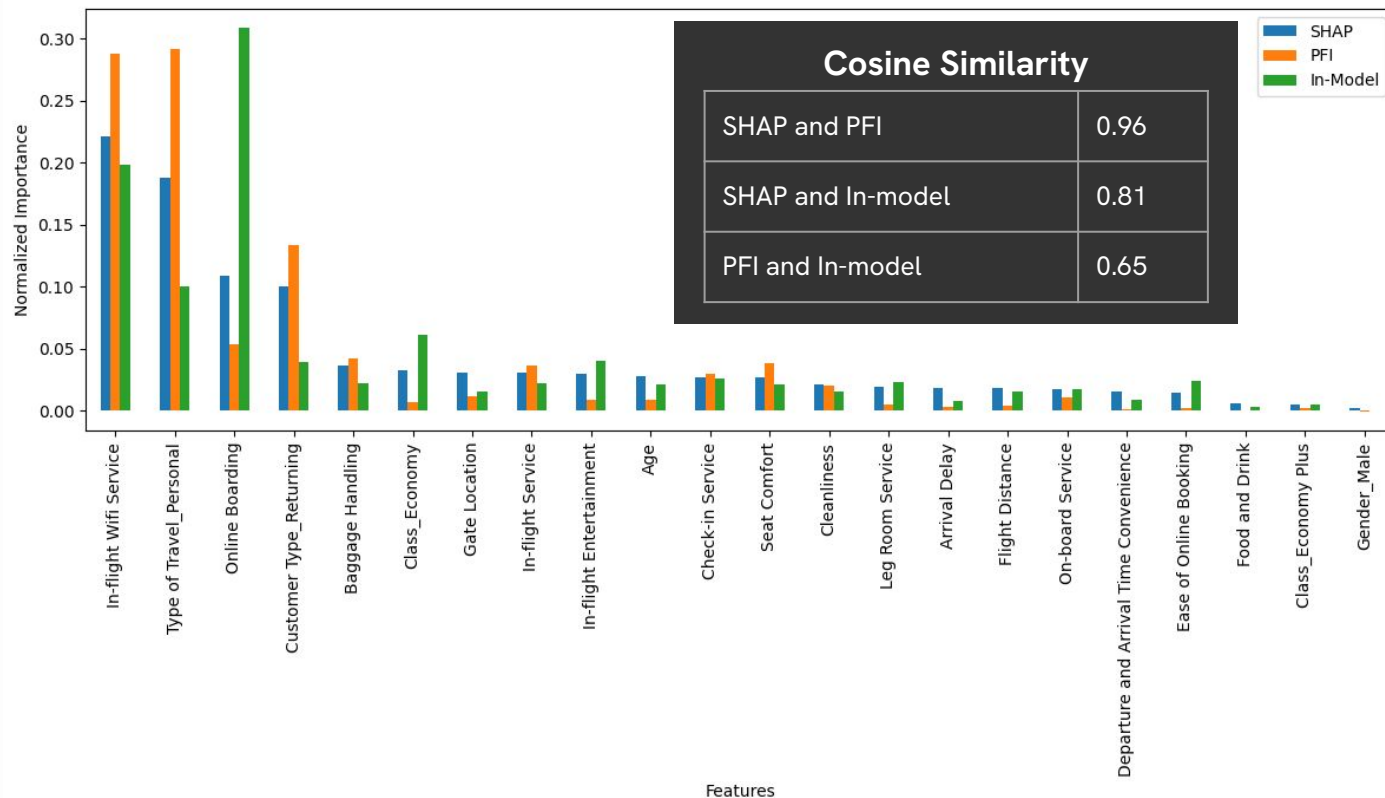


# Permutation Feature Importance

- Does not include if the impact is positive or negative as SHAP does
- Highest Importance:
  - In-flight Wifi Service
  - Type of Travel - Personal
  - Online Boarding
  - Customer type - Returning



# SHAP vs PFI - Global explanations



# Anchors

- Anchors for an instance of each label: obtained with a beam width of 5 and a precision threshold of 95%
- Only instances correctly classified by the black-box model were chosen to explain

## Unsatisfied/Neutral

**On-board Service**  $\leq 4$

**Online Boarding**  $\leq 3$

**Baggage Handling**  $\leq 3$

**Check-in Service**  $\leq 4$

**Precision:** 0.963

**Coverage:** 0.190

## Satisfied

**Baggage Handling**  $\leq 5$

**On-board Service**  $> 4$

**Online Boarding**  $> 2$

**Departure and Arrival Time Convenience**  $\leq 3$

**In-flight Wifi Service**  $\leq 2$

**Leg Room Service**  $> 2$

**Precision:** 0.988

**Coverage:** 0.044

- The rule for the Satisfied instance is more complex and has lower coverage
- This instance is much closer to the decision boundary of the model

# Anchors

The default beam size of 1 leads to bad results. For the same instance, a larger value for this parameter leads to much better coverage results, while keeping the precision.

## Beam width = 1

In-flight Wifi Service  $\leq 3$   
In-flight Entertainment  $\leq 2$   
Online Boarding  $\leq 3$   
Check-in Service  $\leq 3$   
Ease of Online Booking  $\leq 2$

Precision: 0.955  
Coverage: 0.062

## Beam width = 5

On-board Service  $\leq 4$   
Online Boarding  $\leq 3$   
Baggage Handling  $\leq 3$   
Check-in Service  $\leq 4$

Precision: 0.963  
Coverage: 0.190

- Better anchors obtained at the cost of computing time
- Further increases to the beam width would continue to improve the results