Unique-Solution

September 16, 2025

1 BTK Datathon 2025 - Oturum Değer Tahmini

Bu notebook, **Unique()** takımının kullanıcı oturumlarının değerini tahmin etmek için geliştirdiği çözümü içermektedir.

1.1 İçindekiler

1.2 1. Veri Yükleme ve Ön İşleme

[1]:
```python
import polars as pl
import pandas as pd
from sklearnex import patch_sklearn
patch_sklearn()

import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from datetime import datetime, timedelta
import os
from pathlib import Path

# Set up plotting style
plt.style.use('seaborn-v0_8')
sns.set_palette("crest")
warnings.filterwarnings('ignore')

# Configure display options
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
```

```
pd.set_option('display.max_colwidth', None)


DATA_PATH = "./raw_data/"

train = pl.read_csv(f"{DATA_PATH}/train.csv").sort(["user_session",␣
↪"event_time"]).with_columns(pl.lit("train").alias("split"))
test = pl.read_csv(f"{DATA_PATH}/test.csv").sort(["user_session",␣
↪"event_time"]).with_columns(pl.lit("test").alias("split"))
sub = pl.read_csv(f"{DATA_PATH}/sample_submission.csv")
```

```
Extension for Scikit-learn* enabled (https://github.com/uxlfoundation/scikit-
learn-intelex)
```

1.3 2. Veri Keşfi ve Analizi

Analiz Edilen Konular: - Train ve test setlerindeki ürün dağılımları - Ortak ve farklı ürünlerin belirlenmesi
- Oturum değerlerinin analizi - Kullanıcı ve oturum ilişkilerinin incelenmesi

[2]:
```
# Get unique product_ids from train and test sets
train_products = set(train["product_id"].unique().to_list())
test_products = set(test["product_id"].unique().to_list())

# Find products only in train, only in test, and in both
products_only_in_train = train_products - test_products
products_only_in_test = test_products - train_products
products_in_both = train_products & test_products

print(f"Products only in train: {len(products_only_in_train)}")
print(f"Products only in test: {len(products_only_in_test)}")
print(f"Products in both: {len(products_in_both)}")
print(f"Total train products: {len(train_products)}")
print(f"Total test products: {len(test_products)}")
```

```
Products only in train: 11932
Products only in test: 2912
Products in both: 14538
Total train products: 26470
Total test products: 17450
```

Minimum oturum değerinin **5.38** olduğunu ve bu değerin oturumlar arası tekrarlandığını görebiliyoruz.

[3]:
```
train.group_by("user_session").agg(
    pl.col("user_id").n_unique().alias("user_count"),
    pl.col("session_value").first()
    ).sort("session_value", descending=True)
```

[3]:
```
shape: (70_736, 3)

user_session     user_count   session_value
---              ---          ---
str              u32          f64

SESSION_114996   1            2328.66
SESSION_038767   1            1946.93
SESSION_165310   1            1749.42
SESSION_112650   1            1691.01
SESSION_012254   1            1137.33
…                …            …
SESSION_187888   1            5.38
SESSION_188433   1            5.38
SESSION_188692   1            5.38
SESSION_189478   1            5.38
SESSION_189672   1            5.38
```

1.4 3. Veri Ön İşleme ve Hazırlık

- Train ve test verilerinin birleştirilmesi (`full_raw`)
- Zaman damgalarının datetime formatına çevrilmesi
- Kullanıcı-oturum eşleştirmelerinin oluşturulması
- Test ve holdout oturumlarının belirlenmesi
- Kategori ve kullanıcı ID'lerinden sayısal özelliklerin çıkarılması

[4]:
```python
session_target_df = train.unique(subset=["user_session", "session_value"]).
 ↪select(["user_session", "session_value"]).sort(["user_session",␣
 ↪"session_value"])
```

[5]:
```python
full_raw = pl.concat([train.drop("session_value"), test]).sort(["user_session",␣
 ↪"event_time"])
full_raw = full_raw.with_columns(
    pl.col("event_time").str.to_datetime("%Y-%m-%d %H:%M:%S%z", strict=False)
)



session_user_df = full_raw.group_by("user_session", maintain_order=True).agg(
    pl.col("user_id").first().alias("user_id")
)

test_sessions = test["user_session"].unique().to_list()
train_sessions = train["user_session"].unique()
holdout_sessions = train_sessions.filter(train_sessions.is_in(test_sessions)).
 ↪to_list()
```

1.4.1 3.1. Temel Veri Analizi

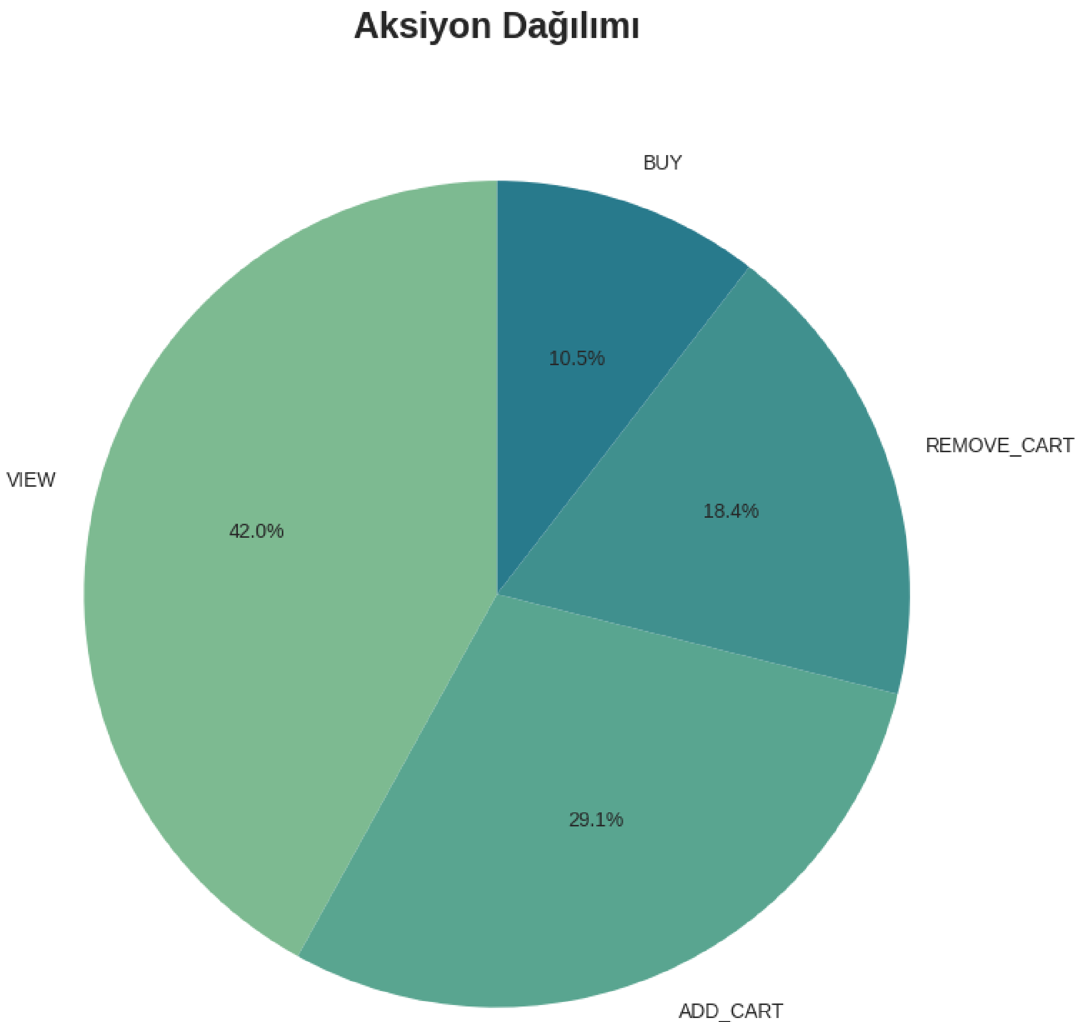
Oturumdaki aksiyonlar, zamansallık ve oturum değeri etiketi üzerine temel görselleştirmelerin yapılması.

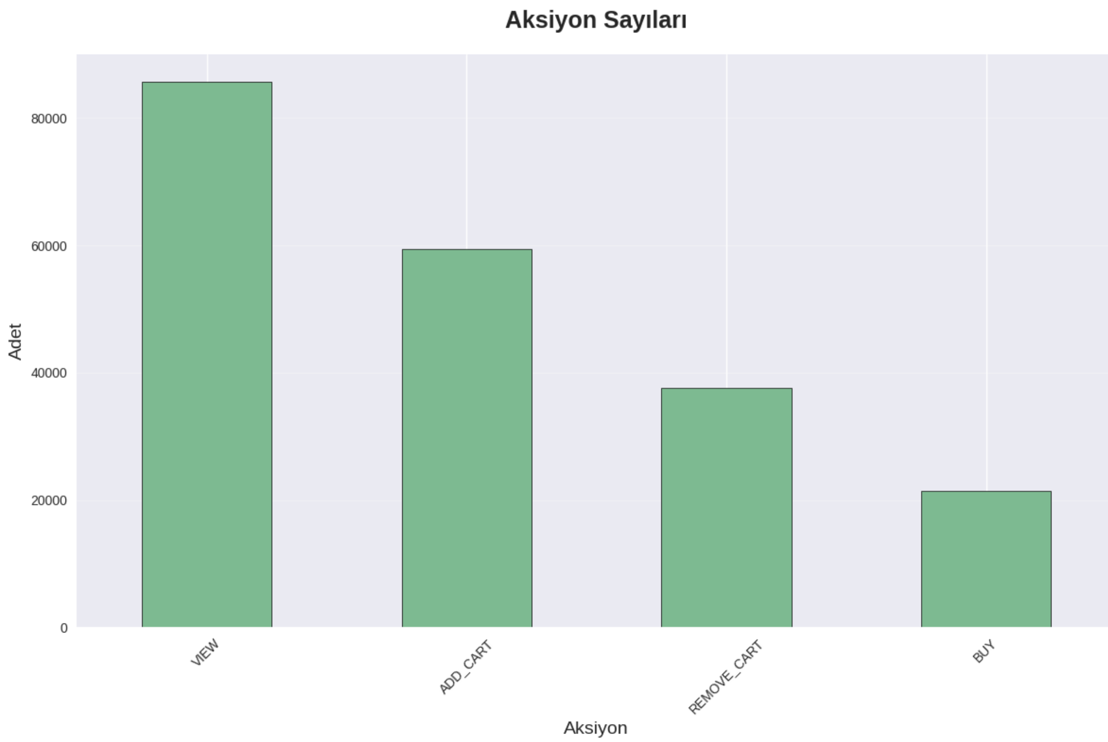
[6]:
```python
def plot_event_type_distribution(raw_train):
    """Create event type distribution pie chart."""
    plt.figure(figsize=(10, 8))
    event_counts = raw_train['event_type'].value_counts()
    plt.pie(event_counts.values, labels=event_counts.index, autopct='%1.1f%%',␣
 ↪startangle=90)
    plt.title('Aksiyon Dağılımı', fontsize=18, fontweight='bold', pad=20)
    plt.tight_layout()
    plt.show()


def plot_event_type_counts(raw_train):
    plt.figure(figsize=(12, 8))
    event_counts = raw_train['event_type'].value_counts()
    event_counts.plot(kind='bar', edgecolor='black', linewidth=0.5)
    plt.title('Aksiyon Sayıları', fontsize=18, fontweight='bold', pad=20)
    plt.xlabel('Aksiyon', fontsize=14)
    plt.ylabel('Adet', fontsize=14)
    plt.xticks(rotation=45)
    plt.grid(axis='y', alpha=0.3)
    plt.tight_layout()
    plt.show()


def plot_session_value_distribution(raw_train):
    plt.figure(figsize=(12, 8))
    plt.hist(raw_train['session_value'], bins=50, alpha=0.7, edgecolor='black',␣
 ↪linewidth=0.5)
    plt.title('Oturum Değer Dağılımı', fontsize=18, fontweight='bold', pad=20)
    plt.xlabel('Oturum Değeri', fontsize=14)
    plt.ylabel('Frekans', fontsize=14)
    plt.grid(axis='y', alpha=0.3)
    plt.tight_layout()
    plt.show()


def plot_daily_events(raw_train):
    plt.figure(figsize=(14, 8))
    daily_events = raw_train.groupby(raw_train['event_time'].dt.date).size()
    daily_events.plot(linewidth=2, marker='o', markersize=4)
    plt.title('Günlük Aksiyon Sayıları', fontsize=18, fontweight='bold', pad=20)
    plt.xlabel('Tarih', fontsize=14)
    plt.ylabel('Aksiyon Sayısı', fontsize=14)
```

```
    plt.grid(True, alpha=0.3)
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()


def plot_hourly_events(raw_train):
    plt.figure(figsize=(12, 8))
    hourly_events = raw_train.groupby(raw_train['event_time'].dt.hour).size()
    hourly_events.plot(kind='bar', edgecolor='black', linewidth=0.5)
    plt.title('Saatlik Aksiyon Dağılımı', fontsize=18, fontweight='bold',␣
 ↪pad=20)
    plt.xlabel('Saat', fontsize=14)
    plt.ylabel('Aksiyon Sayısı', fontsize=14)
    plt.grid(axis='y', alpha=0.3)
    plt.tight_layout()
    plt.show()


def plot_events_by_hour(raw_train):
    plt.figure(figsize=(14, 8))
    event_hour = pd.crosstab(raw_train['event_time'].dt.hour,␣
 ↪raw_train['event_type'])
    event_hour.plot(kind='bar', stacked=True, figsize=(14, 8))
    plt.title('Saate Göre Aksiyon Dağılımı', fontsize=18, fontweight='bold',␣
 ↪pad=20)
    plt.xlabel('Saat', fontsize=14)
    plt.ylabel('Aksiyon Sayısı', fontsize=14)
    plt.legend(title='Aksiyon Tipi', bbox_to_anchor=(1.05, 1), loc='upper left')
    plt.grid(axis='y', alpha=0.3)
    plt.tight_layout()
    plt.show()


def plot_session_value_by_event(raw_train):
    plt.figure(figsize=(12, 8))
    session_value_by_event = raw_train.groupby('event_type')['session_value'].
 ↪mean().sort_values(ascending=False)
    session_value_by_event.plot(kind='bar', edgecolor='black', linewidth=0.5)
    plt.title('Aksiyon Tipine Göre Oturum Değeri', fontsize=18,␣
 ↪fontweight='bold', pad=20)
    plt.xlabel('Aksiyon Tipi', fontsize=14)
    plt.ylabel('Oturum Değeri', fontsize=14)
    plt.xticks(rotation=45)
    plt.grid(axis='y', alpha=0.3)
    plt.tight_layout()
    plt.show()
```

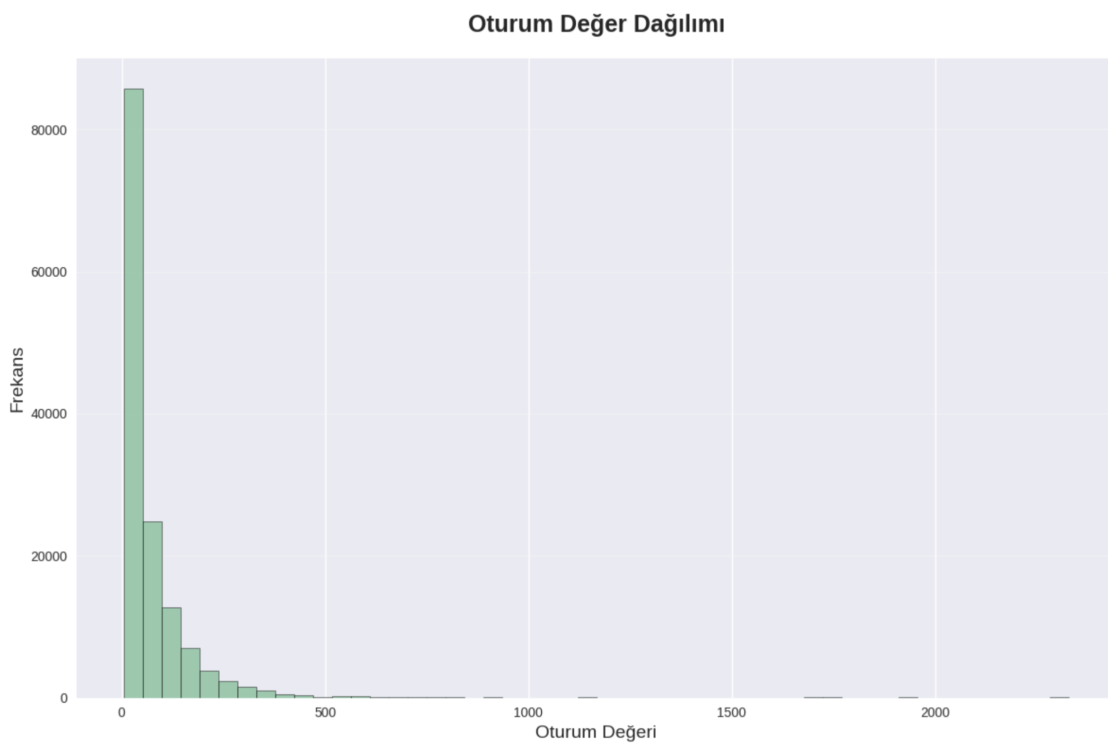
```
def plot_session_length_distribution(raw_train):
    plt.figure(figsize=(12, 8))
    session_lengths = raw_train.groupby('user_session').size()
    plt.hist(session_lengths, bins=50, alpha=0.7, edgecolor='black',␣
↪linewidth=0.5)
    plt.axvline(session_lengths.mean(), linestyle='--', linewidth=2,
                label=f'Ortalama: {session_lengths.mean():.1f}')
    plt.title('Oturum Uzunluğu Dağılımı (Oturum Başına Aksiyon Sayısı)',␣
↪fontsize=18, fontweight='bold', pad=20)
    plt.xlabel('Aksiyon Sayısı', fontsize=14)
    plt.ylabel('Oturum Sayısı', fontsize=14)
    plt.legend(fontsize=12)
    plt.grid(axis='y', alpha=0.3)
    plt.tight_layout()
    plt.show()


def plot_log_session_value_vs_length(raw_train):
    plt.figure(figsize=(12, 8))
    session_stats = raw_train.groupby('user_session').agg({
        'session_value': 'first',
        'event_type': 'count'
    }).rename(columns={'event_type': 'event_count'})

    log_session_value = np.log1p(session_stats['session_value'])

    plt.scatter(session_stats['event_count'], log_session_value,
                alpha=0.6, s=15, edgecolors='black', linewidth=0.3)
    plt.title('Log Oturum Değeri vs Oturum Uzunluğu', fontsize=18,␣
↪fontweight='bold', pad=20)
    plt.xlabel('Oturum Uzunluğu (Aksiyon Sayısı)', fontsize=14)
    plt.ylabel('Log(Oturum Değeri + 1)', fontsize=14)
    plt.grid(True, alpha=0.3)

    plt.tight_layout()
    plt.show()


plot_event_type_distribution(full_raw.to_pandas())
plot_event_type_counts(full_raw.to_pandas())
plot_session_value_distribution(train.to_pandas())
plot_daily_events(full_raw.to_pandas())
plot_hourly_events(full_raw.to_pandas())
plot_events_by_hour(full_raw.to_pandas())
plot_session_value_by_event(train.to_pandas())
```

```
plot_session_length_distribution(full_raw.to_pandas())
plot_log_session_value_vs_length(train.to_pandas())
```

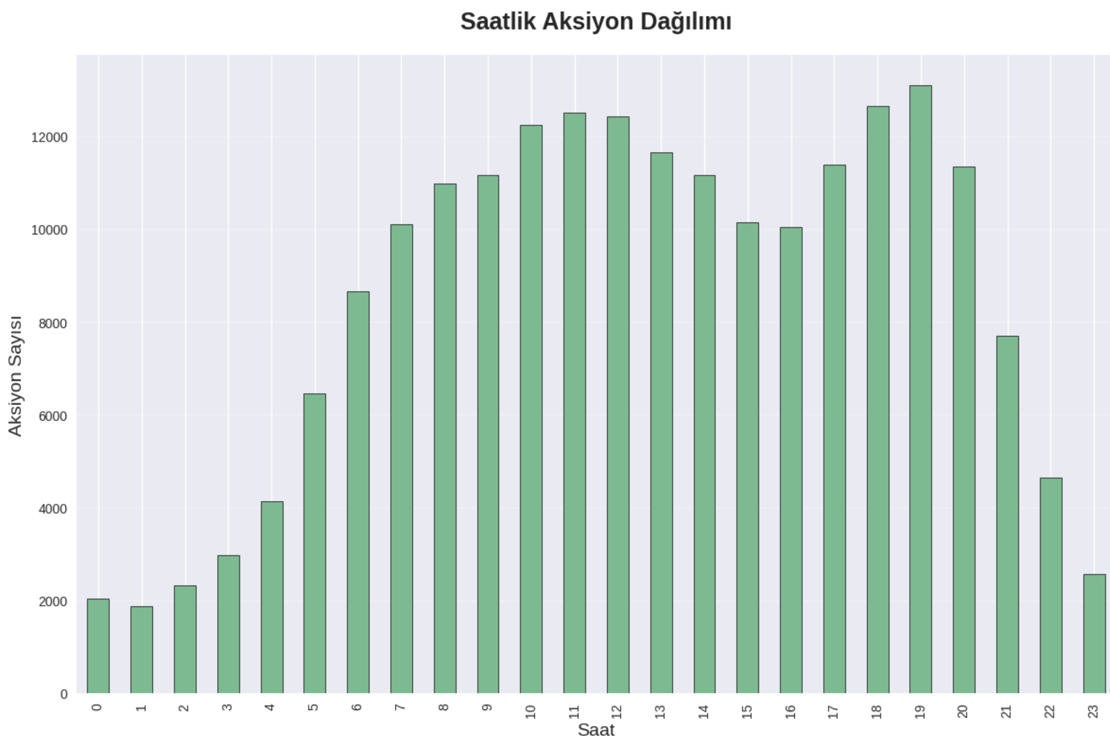




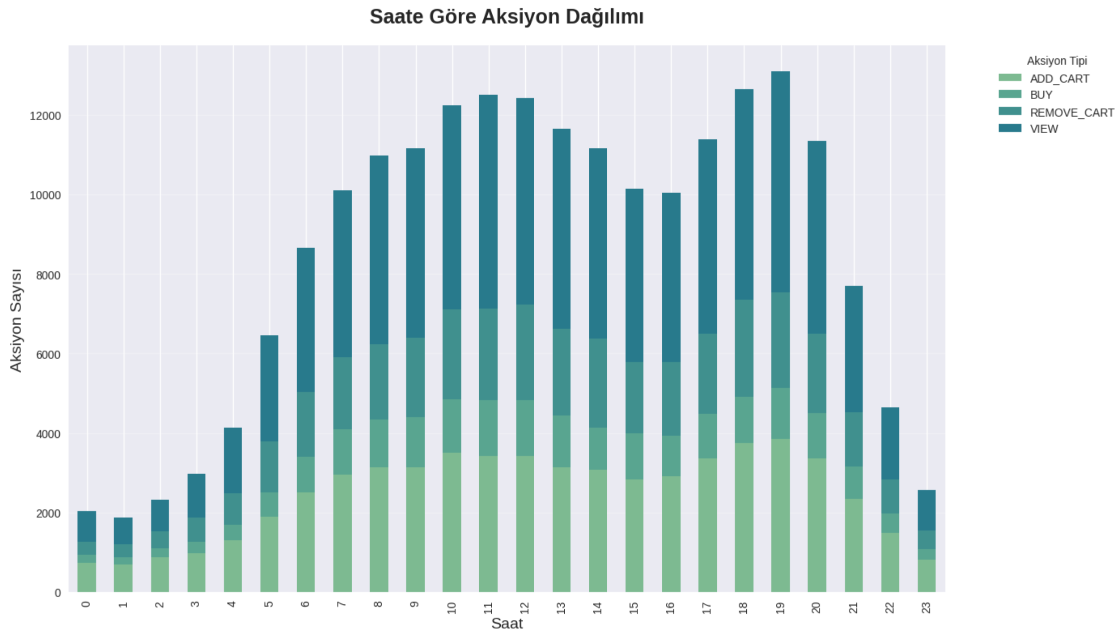
Aksiyon Sayıları
Adet
80000
60000
40000
20000
0
VIEW
ADD_CART
REMOVE_CART
BUY
Aksiyon

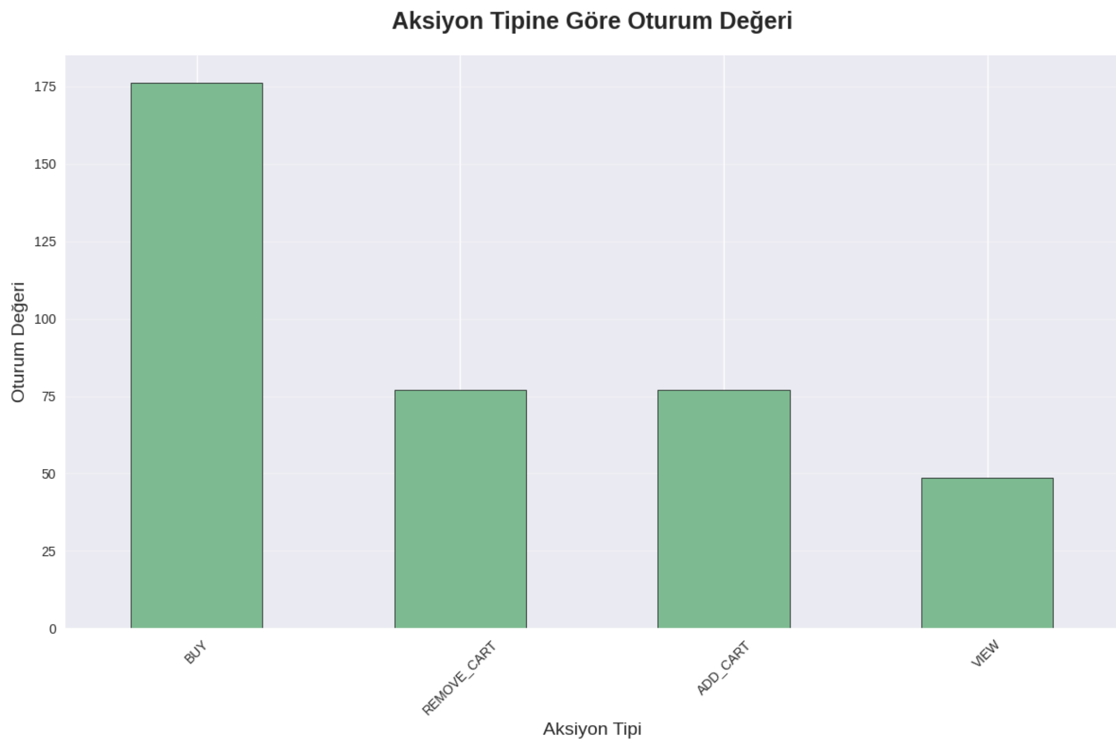


Oturum Değer Dağılımı
Frekans
80000
60000
40000
20000
0
0
500
1000
1500
2000
Oturum Değeri

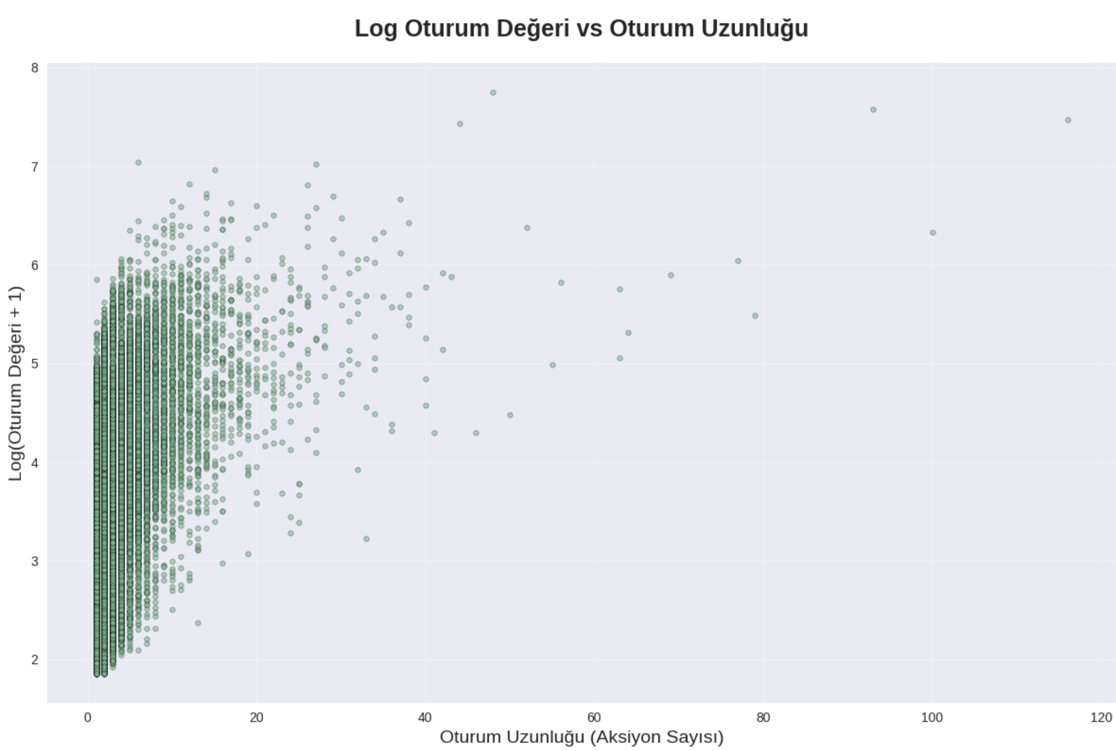



```
<Figure size 1400x800 with 0 Axes>
```


Saate Göre Aksiyon Dağılımı
Aksiyon Tipi
ADD_CART
BUY
REMOVE_CART
VIEW
Aksiyon Sayısı
Saat
0
2000
4000
6000
8000
10000
12000


Aksiyon Tipine Göre Oturum Değeri
Oturum Değeri
Aksiyon Tipi
BUY
REMOVE_CART
ADD_CART
VIEW


Oturum Uzunluğu Dağılımı (Oturum Başına Aksiyon Sayısı)
Ortalama: 2.0
Oturum Sayısı
Aksiyon Sayısı
0
20000
40000
60000
80000
0
20
40
60
80
100
120


Log Oturum Değeri vs Oturum Uzunluğu
Log(Oturum Değeri + 1)
Oturum Uzunluğu (Aksiyon Sayısı)
2
3
4
5
6
7
8
0
20
40
60
80
100
120

1.5 4. Özellik Mühendisliği Fonksiyonları

1.5.1 4.1 Kategori Encoding

- Leave-one-out yaklaşımı ile veri sızıntısını önler
- Kategori bazında ortalama oturum değer istatistikleri hesaplar
- Event türlerine göre ayrıştırılmış özellik çıkarımı yapar

[7]:
```python
def calculate_value_features_optimized(train_df):
    """
    Pre-calculate category value statistics for all sessions efficiently.
    Uses leave-one-out approach to prevent data leakage.
    Split by event_type for more granular features.

    Args:
        train_df: Training data with session_value

    Returns:
        DataFrame with session-level value features
    """
    # Pre-calculate global statistics (session-wise aggregation first)
    session_category_values = train_df.group_by(["user_session", "category_id",␣
↪"event_type"]).agg([
        pl.col("session_value").first().alias("session_value")
    ])

    global_category_stats = session_category_values.group_by(["user_session",␣
↪"category_id", "event_type"]).agg([
        pl.col("session_value").sum().alias("category_total_value"),
        pl.col("session_value").count().alias("category_total_count")
    ]).group_by(["category_id", "event_type"]).agg([
        pl.col("category_total_value").sum(),
        pl.col("category_total_count").sum()
    ])

    # Join global stats to session data
    session_enriched = (
        train_df
        .join(global_category_stats, on=["category_id", "event_type"],␣
↪how="left")
    )

    # Calculate leave-one-out statistics efficiently
    session_value_features = session_enriched.with_columns([
        # Category leave-one-out mean (exclude current session's contribution)
        ((pl.col("category_total_value") - pl.col("session_value")) /
         pl.max_horizontal(pl.col("category_total_count") - 1, 1)).
↪alias("category_mean_value_loo"),
```

```
        # Count features (excluding current session)
        (pl.col("category_total_count") - 1).alias("category_value_count_loo")
    ]).select([
        "user_session", "category_id", "event_type", "session_value",
        "category_mean_value_loo",
        #"category_value_count_loo"
    ])

    return session_value_features

# Calculate frequencies from full_raw data (these don't contain target values␣
↪so no leakage)
category_freq = full_raw.group_by("category_id").agg([
    pl.col("category_id").count().alias("category_frequency")
])

# Pre-calculate value features for all sessions at once
session_value_features = calculate_value_features_optimized(train)
session_value_features.head()
```

[7]: shape: (5, 5)

user_session	category_id	event_type	session_value	category_mean_value_loo
---	---	---	---	---
str	str	str	f64	f64
SESSION_000000	CAT_00144	ADD_CART	355.8	89.577562
SESSION_000000	CAT_00114	REMOVE_CART	355.8	33.532143
SESSION_000000	CAT_00242	ADD_CART	355.8	42.659385
SESSION_000000	CAT_00266	ADD_CART	355.8	70.756034
SESSION_000000	CAT_00268	ADD_CART	355.8	58.241233

1.5.2 4.2 Session İçi Özellik Çıkarımı

- **Oturum İstatistikleri:** Event sayıları, süre, çeşitlilik metrikleri
- **Davranışsal Özellikler:** Dönüşüm oranları, sepet davranışları
- **Temporal Özellikler:** Saat dağılımları, yoğunluk metrikleri
- **Sepet Analizi:** Çoklu ürün sepetleri, kategori çeşitliliği
- **Akış Verimliliği:** Kullanıcı yolculuğu ve davranış skorları

Analizlerimizde oturum içindeki ürün ekleme ve alım yönündeki aksiyonların oturum değeri ile yüksek korelasyona sahip olduğunu gördük. Bunların korelasyon gücüne göre sıralı ağırlıklandırılmış bir toplam aksiyon skoru çıkardığımızda ise bunun modelimizi iyileştirdiğini farkettik. - BUY (4 puan): En değerli eylem, gerçek gelir getiren davranış - ADD_CART (2 puan): Orta değerli eylem, satın alma niyetini gösterir - VIEW (1 puan): Temel eylem, ilgi göstergesi ancak düşük değerli

[8]:
```python
import polars as pl

def create_features(df: pl.DataFrame) -> pl.DataFrame:
    """
    Basit feature engineering - tek DataFrame alıp feature'lı halini döner

    Args:
        df: Raw event data (user_session, event_time, event_type, user_id, etc.)

    Returns:
        DataFrame with session-level features
    """

    # Join product and category frequencies
    df_enriched = (
        df
        .join(category_freq, on="category_id", how="left")
    )

    # Session bazında feature'lar
    features = df_enriched.group_by(["user_session"], maintain_order=True).agg(
        # Event sayıları
        pl.col("event_time").count().alias("session_event_count"),
        pl.col("event_time").first().alias("start_time"),
        (pl.col("event_type") == "VIEW").sum().alias("session_view_count"),
        (pl.col("event_type") == "ADD_CART").sum().
 ↪alias("session_add_cart_count"),
        (pl.col("event_type") == "REMOVE_CART").sum().
 ↪alias("session_remove_cart_count"),
        (pl.col("event_type") == "BUY").sum().alias("session_buy_count"),

        # Session süresi (saniye cinsinden)
        ((pl.col("event_time").max() - pl.col("event_time").min()).dt.
 ↪total_seconds()).alias("session_duration_seconds"),
```

```
        # İlk ve son event tipleri
        pl.col("event_type").first().alias("first_event"),
        pl.col("event_type").last().alias("last_event"),

        # Event tipi çeşitliliği
        pl.col("event_type").n_unique().alias("unique_event_types"),

        # Product feature'ları
        pl.col("product_id").n_unique().alias("unique_products"),
        pl.col("product_id").count().alias("total_product_interactions"),

        # Category feature'ları
        pl.col("category_id").n_unique().alias("unique_categories"),
        pl.col("category_id").count().alias("total_category_interactions"),

    )

    # Join session value features (excluding session_value to prevent leakage)
    session_value_features_no_leak = session_value_features.select([
        "user_session", "category_id", "event_type",
        "category_mean_value_loo",
    ])

    # Aggregate session value features by session and event_type
    session_value_agg = session_value_features_no_leak.
↪group_by(["user_session"], maintain_order=True).agg([

        # Category mean value aggregations by event_type
        pl.col("category_mean_value_loo").filter(pl.col("event_type") ==␣
↪"VIEW").sum().alias("sum_category_mean_value_loo_view"),
        pl.col("category_mean_value_loo").filter(pl.col("event_type") ==␣
↪"ADD_CART").sum().alias("sum_category_mean_value_loo_add_cart"),
        pl.col("category_mean_value_loo").filter(pl.col("event_type") ==␣
↪"REMOVE_CART").sum().alias("sum_category_mean_value_loo_remove_cart"),
        pl.col("category_mean_value_loo").filter(pl.col("event_type") == "BUY").
↪sum().alias("sum_category_mean_value_loo_buy"),
    ])

    # Net cart calculation per product within session, then summed
    net_cart_features = df_enriched.group_by(["user_session", "product_id"],␣
↪maintain_order=True).agg([
        (pl.col("event_type") == "ADD_CART").sum().alias("product_add_cart"),
        (pl.col("event_type") == "REMOVE_CART").sum().
↪alias("product_remove_cart"),
    ]).with_columns([
```

```
        (pl.col("product_add_cart") - pl.col("product_remove_cart")).
↪alias("product_net_cart")
    ]).group_by("user_session").agg([
        pl.col("product_net_cart").sum().alias("session_net_cart_count"),
        (pl.col("product_net_cart") > 0).sum().
↪alias("session_net_cart_unique_products"),
    ])

    # Multi-product basket features (same timestamp BUY events)
    basket_features = df_enriched.filter(pl.col("event_type") == "BUY").
↪group_by(["user_session", "event_time"], maintain_order=True).agg([
        pl.col("product_id").count().alias("products_in_basket"),
        pl.col("category_id").n_unique().alias("categories_in_basket"),
    ]).group_by("user_session").agg([
        # Basket transaction features
        pl.col("products_in_basket").count().alias("basket_transaction_count"),
        pl.col("products_in_basket").max().alias("max_basket_size"),
        pl.col("products_in_basket").mean().alias("avg_basket_size"),
        pl.col("products_in_basket").sum().alias("total_basket_products"),

        # Multi-product basket indicators
        (pl.col("products_in_basket") > 1).sum().alias("multi_product_baskets"),
        (pl.col("products_in_basket") == 1).sum().
↪alias("single_product_baskets"),

        # Category diversity in baskets
        pl.col("categories_in_basket").max().alias("max_categories_per_basket"),
        pl.col("categories_in_basket").mean().
↪alias("avg_categories_per_basket"),

        # Basket complexity score
        (pl.col("products_in_basket") * pl.col("categories_in_basket")).max().
↪alias("max_basket_complexity"),
        (pl.col("products_in_basket") * pl.col("categories_in_basket")).mean().
↪alias("avg_basket_complexity"),
    ])

    # Ratio feature'ları ayrı hesapla
    features = features.with_columns([
        # Product ratios
        (pl.col("total_product_interactions") / pl.col("session_event_count")).
↪alias("product_interaction_rate"),
        (pl.col("unique_products") / pl.col("session_event_count")).
↪alias("product_diversity"),

        # Category ratios
```

```
        (pl.col("total_category_interactions") / pl.col("session_event_count")).
↪alias("category_interaction_rate"),
        (pl.col("unique_categories") / pl.col("session_event_count")).
↪alias("category_diversity"),
        (pl.col("unique_categories") / (pl.col("unique_products") + 1e-8)).
↪alias("category_product_ratio"),

        # Conversion Metrics
        (pl.col("session_buy_count") / (pl.col("session_add_cart_count") +␣
↪1e-8)).alias("cart_to_purchase_rate"),
        (pl.col("session_add_cart_count") / (pl.col("session_view_count") +␣
↪1e-8)).alias("view_to_cart_rate"),
        (pl.col("session_buy_count") / pl.col("session_event_count")).
↪alias("overall_conversion_rate"),

        # Cart Behavior
        (pl.col("session_add_cart_count") - pl.col("session_buy_count")).
↪alias("cart_abandonment_count"),
        (pl.col("session_remove_cart_count") / (pl.
↪col("session_add_cart_count") + 1e-8)).alias("cart_removal_rate"),

        # User Engagement
        ((pl.col("session_buy_count") + pl.col("session_add_cart_count")) / pl.
↪col("session_event_count")).alias("goal_oriented_ratio"),
        (pl.col("session_view_count") / pl.col("session_event_count")).
↪alias("browsing_ratio"),

        # Product/Category Patterns
        (pl.col("unique_products") / (pl.col("unique_categories") + 1e-8)).
↪alias("products_per_category"),
        (pl.col("unique_categories") / (pl.col("unique_products") + 1e-8)).
↪alias("categories_per_product"),

        # Last event indicator
        (pl.col("last_event") == "BUY").alias("last_event_is_purchase"),


        # Session positive event score
        (pl.col("session_buy_count")*4 + pl.col("session_add_cart_count")*2 +␣
↪pl.col("session_view_count")*1).alias("session_positive_event_score"),

    ])


    # Temporal features
```

```
  temporal_features = df_enriched.group_by(["user_session"],␣
↪maintain_order=True).agg([
      pl.col("event_time").dt.hour().first().alias("session_start_hour"),
      pl.col("event_time").dt.weekday().first().
↪alias("session_start_weekday"),
  ])

  # Session intensity features
  intensity_features = df_enriched.group_by(["user_session"],␣
↪maintain_order=True).agg([
      (pl.col("event_time").count() / ((pl.col("event_time").max() - pl.
↪col("event_time").min()).dt.total_seconds() / 60 + 1e-8)).
↪alias("events_per_minute"),
      (pl.col("event_time").count() / ((pl.col("event_time").max() - pl.
↪col("event_time").min()).dt.total_seconds() / 3600 + 1e-8)).
↪alias("events_per_hour"),
  ])

  # Additional simple features
  additional_features = df_enriched.group_by(["user_session"],␣
↪maintain_order=True).agg([
      # Session duration in minutes
      ((pl.col("event_time").max() - pl.col("event_time").min()).dt.
↪total_seconds() / 60).alias("session_duration_minutes"),
  ])

  # Event transition patterns ve flow efficiency
  transition_features = df_enriched.group_by(["user_session"],␣
↪maintain_order=True).agg([
      # Flow efficiency features
      pl.when(pl.col("event_type").first() == "VIEW").then(pl.lit(1))
      .when(pl.col("event_type").first() == "ADD_CART").then(pl.lit(2))
      .when(pl.col("event_type").first() == "BUY").then(pl.lit(3))
      .otherwise(pl.lit(0)).alias("session_start_efficiency"),

      pl.when(pl.col("event_type").last() == "BUY").then(pl.lit(3))
      .when(pl.col("event_type").last() == "ADD_CART").then(pl.lit(2))
      .when(pl.col("event_type").last() == "VIEW").then(pl.lit(1))
      .otherwise(pl.lit(0)).alias("session_end_efficiency"),

      # Session flow score (higher = more efficient)
      pl.when((pl.col("event_type").first() == "VIEW") & (pl.
↪col("event_type").last() == "BUY")).then(pl.lit(3))
      .when((pl.col("event_type").first() == "VIEW") & (pl.col("event_type").
↪last() == "ADD_CART")).then(pl.lit(2))
```

```
        .when((pl.col("event_type").first() == "ADD_CART") & (pl.
↪col("event_type").last() == "BUY")).then(pl.lit(2))
        .when((pl.col("event_type").first() == "VIEW") & (pl.col("event_type").
↪last() == "VIEW")).then(pl.lit(1))
        .otherwise(pl.lit(0)).alias("session_flow_score"),

        # Session depth (how deep user goes in funnel)
        pl.when((pl.col("event_type") == "BUY").sum() > 0).then(pl.lit(3))
        .when((pl.col("event_type") == "ADD_CART").sum() > 0).then(pl.lit(2))
        .when((pl.col("event_type") == "VIEW").sum() > 0).then(pl.lit(1))
        .otherwise(pl.lit(0)).alias("session_depth"),
    ])

    # Tüm feature'ları birleştir
    final_features = (
        features
        .join(session_value_agg, on=["user_session"], how="left")
        .join(net_cart_features, on=["user_session"], how="left")
        .join(basket_features, on=["user_session"], how="left")
        .join(temporal_features, on=["user_session"], how="left")
        .join(intensity_features, on=["user_session"], how="left")
        .join(additional_features, on=["user_session"], how="left")
        .join(transition_features, on=["user_session"], how="left")
    )

    # Add value-based features after joining session value aggregations
    final_features = final_features.with_columns([

        # Category value based features by event_type
        (pl.col("sum_category_mean_value_loo_view") / (pl.
↪col("session_view_count") + 1e-8)).alias("weighted_category_value_loo_view"),
        (pl.col("sum_category_mean_value_loo_add_cart") / (pl.
↪col("session_add_cart_count") + 1e-8)).
↪alias("weighted_category_value_loo_add_cart"),
        (pl.col("sum_category_mean_value_loo_remove_cart") / (pl.
↪col("session_remove_cart_count") + 1e-8)).
↪alias("weighted_category_value_loo_remove_cart"),
        (pl.col("sum_category_mean_value_loo_buy") / (pl.
↪col("session_buy_count") + 1e-8)).alias("weighted_category_value_loo_buy"),

        # Basket behavior ratios
        (pl.col("multi_product_baskets") / (pl.col("basket_transaction_count")␣
↪+ 1e-8)).alias("multi_basket_ratio"),
        (pl.col("single_product_baskets") / (pl.col("basket_transaction_count")␣
↪+ 1e-8)).alias("single_basket_ratio"),
```

```
        # Basket efficiency features
        (pl.col("total_basket_products") / (pl.col("basket_transaction_count")␣
↪+ 1e-8)).alias("products_per_transaction"),
        (pl.col("max_basket_size") / (pl.col("unique_products") + 1e-8)).
↪alias("max_basket_coverage"),

        # Shopping pattern indicators
        pl.when(pl.col("multi_product_baskets").fill_null(0) > 0).then(pl.
↪lit(1)).otherwise(pl.lit(0)).alias("has_multi_product_baskets"),
        pl.when(pl.col("max_basket_size").fill_null(0) >= 3).then(pl.lit(1)).
↪otherwise(pl.lit(0)).alias("has_large_baskets"),
    ])

    return final_features
```

[9]:
```
agg_df = create_features(full_raw)
```

1.5.3 4.3 Geçmiş ve Genel Davranış Özellikleri

- **Kümülatif Metrikler:** Toplam event, görüntüleme, satın alma sayıları
- **Geçmiş Ortalamalar:** Oturum uzunluğu, süre, aktivite ortalamaları

- **Dönüşüm Oranları:** Görüntülemeden satın almaya, sepete ekleme oranları
- **Davranış Tutarlılığı:** Mevcut oturumun geçmiş ortalamalara oranı
- **Kalite Metrikleri:** Oturum akışı, derinlik, verimlilik skorları
- **Sepet Geçmişi:** Çoklu ürün sepeti alışkanlıkları

Veriseti sentetik olduğu için kullanıcı alışkanlıklarının durağan ve ekstrapole edilebilir olduğunu gördük. Bu yüzden ürettiğimiz bazı öznitelikler look-ahead leak içeriyor.

[10]:
```
historical_feat_df = (
    agg_df
    .join(session_user_df, on="user_session", how="left")
    .join(session_target_df, on="user_session", how="left")
    .sort("user_id", "start_time")
    .with_columns([
        pl.col("session_event_count").cum_sum().over("user_id").
↪alias("cumsum_session_event_count"),
        pl.col("session_view_count").cum_sum().over("user_id").
↪alias("cumsum_session_view_count"),
        pl.col("session_add_cart_count").cum_sum().over("user_id").
↪alias("cumsum_session_add_cart_count"),
        pl.col("session_remove_cart_count").cum_sum().over("user_id").
↪alias("cumsum_session_remove_cart_count"),
        pl.col("session_buy_count").cum_sum().over("user_id").
↪alias("cumsum_session_buy_count"),
```

```
        pl.col("session_positive_event_score").sum().over("user_id").
↪alias("sum_session_positive_event_score"),

        # Historical means
        pl.col("session_event_count").mean().over("user_id").
↪alias("historical_mean_session_event_count"),
        pl.col("session_view_count").mean().over("user_id").
↪alias("historical_mean_session_view_count"),
        pl.col("session_add_cart_count").mean().over("user_id").
↪alias("historical_mean_session_add_cart_count"),
        pl.col("session_remove_cart_count").mean().over("user_id").
↪alias("historical_mean_session_remove_cart_count"),
        # pl.col("session_net_cart_count").mean().over("user_id").
↪alias("historical_mean_session_net_cart_count"),
        pl.col("session_buy_count").mean().over("user_id").
↪alias("historical_mean_session_buy_count"),

        # Historical conversion rates (CR) and click-through rates (CTR)
        (pl.col("session_buy_count").cum_sum().over("user_id") / pl.
↪col("session_view_count").cum_sum().over("user_id")).
↪alias("historical_view_to_buy_cr"),
        (pl.col("session_add_cart_count").cum_sum().over("user_id") / pl.
↪col("session_view_count").cum_sum().over("user_id")).
↪alias("historical_view_to_cart_ctr"),
        (pl.col("session_buy_count").cum_sum().over("user_id") / pl.
↪col("session_add_cart_count").cum_sum().over("user_id")).
↪alias("historical_cart_to_buy_cr"),
        (pl.col("session_buy_count").cum_sum().over("user_id") / pl.
↪col("session_event_count").cum_sum().over("user_id")).
↪alias("historical_buy_to_total_rate"),
        (pl.col("session_remove_cart_count").cum_sum().over("user_id") / pl.
↪col("session_add_cart_count").cum_sum().over("user_id")).
↪alias("historical_cart_abandonment_rate"),

        # Historical session counts
        pl.int_range(pl.len()).over("user_id").
↪alias("historical_session_count") + 1,

        # Session Momentum Features - Above average indicators
        pl.when(pl.col("session_event_count") > pl.col("session_event_count").
↪mean().over("user_id")).then(pl.lit(1)).otherwise(pl.lit(0)).
↪alias("above_avg_session_length"),
        pl.when(pl.col("session_duration_seconds") > pl.
↪col("session_duration_seconds").mean().over("user_id")).then(pl.lit(1)).
↪otherwise(pl.lit(0)).alias("above_avg_session_duration"),
```

```
        pl.when(pl.col("unique_products") > pl.col("unique_products").mean().over("user_id")).then(pl.lit(1)).otherwise(pl.lit(0)).alias("above_avg_product_diversity"),
        pl.when(pl.col("unique_categories") > pl.col("unique_categories").mean().over("user_id")).then(pl.lit(1)).otherwise(pl.lit(0)).alias("above_avg_category_diversity"),

        # User Behavior Consistency - Ratios to historical means
        (pl.col("session_event_count") / pl.col("session_event_count").mean().over("user_id")).alias("session_length_ratio"),
        (pl.col("session_duration_seconds") / pl.col("session_duration_seconds").mean().over("user_id")).alias("session_duration_ratio"),
        (pl.col("unique_products") / pl.col("unique_products").mean().over("user_id")).alias("product_diversity_ratio"),
        (pl.col("unique_categories") / pl.col("unique_categories").mean().over("user_id")).alias("category_diversity_ratio"),

        # Historical Session Quality Metrics
        pl.col("session_flow_score").mean().over("user_id").alias("historical_mean_session_flow"),
        pl.col("session_depth").mean().over("user_id").alias("historical_mean_session_depth"),
        pl.col("session_start_efficiency").mean().over("user_id").alias("historical_mean_session_start_efficiency"),
        pl.col("session_end_efficiency").mean().over("user_id").alias("historical_mean_session_end_efficiency"),

        # Historical Conversion Efficiency
        (pl.col("session_add_cart_count").cum_sum().over("user_id") / pl.col("session_event_count").cum_sum().over("user_id")).alias("historical_cart_engagement_rate"),
        (pl.col("session_add_cart_count").sum() / pl.col("session_event_count").sum()).alias("historical_mean_cart_engagement_rate"),

        pl.col("has_multi_product_baskets").mean().over("user_id").alias("historical_mean_has_multi_product_baskets"),
        pl.col("has_large_baskets").mean().over("user_id").alias("historical_mean_has_large_baskets"),
        pl.col("has_multi_product_baskets").sum().over("user_id").alias("sum_has_multi_product_baskets"),
        pl.col("has_large_baskets").sum().over("user_id").alias("sum_has_large_baskets"),
        pl.col("max_basket_coverage").sum().over("user_id").alias("sum_max_basket_coverage"),
```

```
        # Historical Trend Indicators
        pl.when(pl.col("session_event_count") > pl.col("session_event_count").shift(1).over("user_id")).then(pl.lit(1))
        .when(pl.col("session_event_count") < pl.col("session_event_count").shift(1).over("user_id")).then(pl.lit(-1))
        .otherwise(pl.lit(0)).alias("session_length_trend"),

        pl.when(pl.col("session_duration_seconds") > pl.col("session_duration_seconds").shift(1).over("user_id")).then(pl.lit(1))
        .when(pl.col("session_duration_seconds") < pl.col("session_duration_seconds").shift(1).over("user_id")).then(pl.lit(-1))
        .otherwise(pl.lit(0)).alias("session_duration_trend"),

    ])
    .select([
        "user_session",
        "user_id",
        "sum_session_positive_event_score",

        # Historical means
        "historical_mean_session_event_count", "historical_mean_session_view_count",
        "historical_mean_session_add_cart_count", "historical_mean_session_remove_cart_count",
        "historical_mean_session_buy_count",

        # Historical conversion rates
        "historical_view_to_buy_cr", "historical_view_to_cart_ctr",
        "historical_cart_to_buy_cr", "historical_buy_to_total_rate", "historical_cart_abandonment_rate",

        # Session count
        "historical_session_count",

        # Behavior consistency ratios
        "session_length_ratio", "session_duration_ratio", "product_diversity_ratio", "category_diversity_ratio",

        # Historical quality metrics
        "historical_mean_session_flow", "historical_mean_session_depth", "historical_mean_session_start_efficiency", "historical_mean_session_end_efficiency",

        # Historical efficiency
        "historical_cart_engagement_rate",
```

```
        # Historical basket metrics
        "sum_has_multi_product_baskets", "sum_has_large_baskets",
        "sum_max_basket_coverage",
    ])
)
```

1.6 5. Veri Seti Hazırlama

- **final_train_df:** Eğitim verisi (session_value hedef değişkeni ile)
- **final_test_df:** Test verisi (tahmin yapılacak oturumlar)

Birleştirme İşlemleri: - Temel özellikler + Geçmiş davranış özellikleri - Kullanıcı-oturum eşleştirmeleri - Hedef değişken (session_value) eklenmesi

[11]:
```
final_train_df = (
    agg_df
    .filter(pl.col("user_session").is_in(train_sessions))
    .join(session_user_df, on="user_session", how="left")
    .join(historical_feat_df.drop("user_id"), on="user_session", how="left")
    .join(session_target_df, on="user_session", how="left")
)
```

[12]:
```
final_test_df = (
    agg_df
    .filter(pl.col("user_session").is_in(test_sessions))
    .join(session_user_df, on="user_session", how="left")
    .join(historical_feat_df.drop("user_id"), on="user_session", how="left")
)
```

1.7 6. Model Eğitimi ve CV

Hedef Değişken Dönüşümü Tahmin edilen değer üst sınırı olmayan bir değer. Oturum içindeki ürün sayısı arttıkça oturumun değeri de üst sınırı olmayan şekilde artacak. Üst sınırsızlık durumu ağaç temelli modeller için bir problem oluşturuyor. Ağaçlar extrapolation senaryosuna çalışmaya elverişli olmadıkları için etiket değerimizi doğrudan oturum değeri olarak değil, oturum değerinin değerle korelasyonu yüksek aksiyon sayılarına oranı olarak seçtik. Yarışma esnasında gözle görülür bir iyileşmeyi de bu değişiklik ile aldık. - **Katsayı Tahmini:** `session_value / session_positive_event_score` - **Geri Dönüşüm:** Tahmin × katsayı = session_value - NaN ve Inf değerler için önlem

1.7.1 6.1 CV Stratejisi

- **StratifiedGroupKFold:** Kullanıcı bazlı gruplamalar ile 10-fold CV
- **Hedefi Düzgün Dağıtma:** Katsayı değerlerin quantile'larına göre stratification
- **Grup Korunumu:** Aynı kullanıcıya ait oturumlar farklı foldlara dağılmıyor

[ ]:
```
from sklearn.model_selection import GroupKFold, KFold, StratifiedGroupKFold
```

```
# Create stratified bins for the coefficient target
temp_train_df = final_train_df.with_columns([
    pl.col("session_positive_event_score").fill_nan(1).map_elements(lambda x: 1␣
 ↪if x == float('inf') or x == float('-inf') else x, return_dtype=pl.Float64).
 ↪clip(lower_bound=5.3).alias("predcoeff")
])
coeff_values = (temp_train_df["session_value"] / temp_train_df["predcoeff"]).
 ↪to_pandas()
stratified_bins = pd.qcut(coeff_values, q=10, labels=False)

cv_splits = list(StratifiedGroupKFold(n_splits=10, shuffle=True,␣
 ↪random_state=1).split(
    final_train_df,
    y=stratified_bins,
    groups=final_train_df["user_id"]
))
```

1.8 6.2 Model Eğitimi

1.8.1 6.2.1 Model Blending

VotingRegressor ile Birleştirilen Modeller: - **LightGBM Model 1:** Tweedie 1.11 power ile - **LightGBM Model 2:** Standard Tweedie ile - **CatBoost Model:** RMSE objektifi ile

1.9 6.3 Model Validasyonu

1.9.1 6.3.1 Model Performans Değerlendirmesi

- **Fold Bazında MSE:** Her fold için ayrı performans metrigi
- **Overall OOF MSE:** Tüm out-of-fold tahminlerin genel performansı

[ ]:
```
import lightgbm as lgb
from lightgbm import LGBMRegressor
from sklearn.metrics import mean_squared_error
from sklearn.ensemble import VotingRegressor
import numpy as np
from catboost import CatBoostRegressor
from xgboost import XGBRegressor
import pandas as pd

cat_features = [
    "first_event", "last_event",
    ]

# Define multiple parameter sets for blending
lgb_params_1 = {
    'objective': 'tweedie',
    'tweedie_variance_power': 1.11,
```

```
    'metric': 'mse',
    'boosting_type': 'gbdt',
    'n_estimators': 1000,
    'max_depth': 3,
    'feature_fraction': 0.7,
    'bagging_fraction': 0.7,
    'bagging_freq': 20,
    'random_state': 1,
    'verbose': -1
}

lgb_params_2 = {
    'objective': 'tweedie',
    'metric': 'mse',
    'boosting_type': 'gbdt',
    'n_estimators': 1000,
    'max_depth': 3,
    'feature_fraction': 0.7,
    'bagging_fraction': 0.7,
    'bagging_freq': 20,
    'random_state': 1,
    'verbose': -1
}

catboost_params = {
    'iterations': 1000,
    'depth': 6,
    # 'learning_rate': 0.1,
    'loss_function': 'RMSE',
    'random_seed': 1,
    'cat_features': cat_features,
    'verbose': False
}

feature_list = [c for c in final_train_df.columns
                if c not in ["user_id", "user_session", "session_value",␣
 ↪"start_time"]]

fold_scores = []
models = []
coefficients = []
oof_predictions = np.zeros(len(final_train_df))

for fold, (train_idx, val_idx) in enumerate(cv_splits):
    print(f"Fold {fold+1}...")
    train_data = final_train_df[train_idx]
    val_data   = final_train_df[val_idx]
```

```
train_data = train_data.with_columns([
    pl.col("session_positive_event_score").fill_nan(1).map_elements(lambda␣
↪x: 1 if x == float('inf') or x == float('-inf') else x, return_dtype=pl.
↪Float64).clip(lower_bound=5.3).alias("predcoeff")
]).fill_nan(0)

# Replace all infs with 0 in the entire dataframe
for col in train_data.columns:
    if train_data[col].dtype in [pl.Float64, pl.Float32, pl.Int64, pl.
↪Int32, pl.Int16, pl.Int8, pl.UInt64, pl.UInt32, pl.UInt16, pl.UInt8]:
        train_data = train_data.with_columns([
            pl.col(col).map_elements(lambda x: 0 if x == float('inf') or x␣
↪== float('-inf') else x, return_dtype=pl.Float64)
        ])

val_data = val_data.with_columns([
    pl.col("session_positive_event_score").fill_nan(1).map_elements(lambda␣
↪x: 1 if x == float('inf') or x == float('-inf') else x, return_dtype=pl.
↪Float64).clip(lower_bound=5.3).alias("predcoeff")
]).fill_nan(0)

for col in val_data.columns:
    if val_data[col].dtype in [pl.Float64, pl.Float32, pl.Int64, pl.Int32,␣
↪pl.Int16, pl.Int8, pl.UInt64, pl.UInt32, pl.UInt16, pl.UInt8]:
        val_data = val_data.with_columns([
            pl.col(col).map_elements(lambda x: 0 if x == float('inf') or x␣
↪== float('-inf') else x, return_dtype=pl.Float64)
        ])

X_train = train_data[feature_list].to_pandas()
X_val   = val_data[feature_list].to_pandas()

# Kategorikler
if len(cat_features) > 0:
    X_train[cat_features] = X_train[cat_features].astype("category")
    X_val[cat_features]   = X_val[cat_features].astype("category")

# Target is now the coefficient (session_value /␣
↪session_positive_event_score)
y_train_coeff = (train_data["session_value"] / train_data["predcoeff"])
y_val_coeff = (val_data["session_value"] / val_data["predcoeff"])

model1 = LGBMRegressor(**lgb_params_1)
model2 = LGBMRegressor(**lgb_params_2)
model3 = CatBoostRegressor(**catboost_params)
```

```
    voting_model = VotingRegressor(
        estimators=[
            ('lgb_1', model1),
            ('lgb_2', model2),
            ('catboost', model3),
        ]
    )

    # Fit the voting regressor to predict coefficient
    voting_model.fit(X_train, y_train_coeff)

    # Make predictions for coefficient
    y_pred_coeff = voting_model.predict(X_val)

    # Convert coefficient predictions back to session_value for metric␣
 ↪calculation
    y_pred_session_value = y_pred_coeff * val_data["predcoeff"]
    y_val_session_value = val_data["session_value"].to_pandas()

    # Store out-of-fold predictions (in session_value scale)
    oof_predictions[val_idx] = y_pred_session_value

    mse = mean_squared_error(y_val_session_value, y_pred_session_value)
    print(f"Fold {fold+1} Voting MSE (session_value): {mse:.4f}")

    fold_scores.append(mse)
    models.append(voting_model)

print(f"Mean Voting MSE: {np.mean(fold_scores):.4f}")

# Calculate overall OOF MSE
oof_mse = mean_squared_error(final_train_df["session_value"].to_pandas(),␣
 ↪oof_predictions)
print(f"Overall OOF MSE: {oof_mse:.4f}")
```

```
Fold 1…
Fold 1 Voting MSE (session_value): 163.9635
Fold 2…
Fold 2 Voting MSE (session_value): 175.7411
Fold 3…
Fold 3 Voting MSE (session_value): 154.5049
Fold 4…
Fold 4 Voting MSE (session_value): 143.0390
Fold 5…
Fold 5 Voting MSE (session_value): 176.0720
Fold 6…
```

```
Fold 6 Voting MSE (session_value): 170.7661
Fold 7…
Fold 7 Voting MSE (session_value): 161.0198
Fold 8…
Fold 8 Voting MSE (session_value): 153.4139
Fold 9…
Fold 9 Voting MSE (session_value): 151.0912
Fold 10…
Fold 10 Voting MSE (session_value): 165.8822
Mean Voting MSE: 161.5494
Overall OOF MSE: 161.5827
```

[16]:
```python
fold_scores
```

[16]:
```
[163.96352778719455,
 175.74114028789597,
 154.50490616446422,
 143.03902231047908,
 176.07201734941697,
 170.76613867019915,
 161.0198237459633,
 153.41390272016613,
 151.09124555804172,
 165.88219325735173]
```

[17]:
```python
print(f"Mean Voting MSE: {np.mean(fold_scores):.4f}")
```

```
Mean Voting MSE: 161.5494
```

1.10 7. Tahminlerin Üretilmesi

- Yarışma submission için test seti tahminleri
- Tüm fold modellerinin ortalaması
- Alt sınır (5.0) uygulaması

[18]:
```python
test_preds = []

final_test_df = final_test_df.with_columns([
    pl.col("session_positive_event_score").fill_nan(1).map_elements(lambda x: 1␣
↪if x == float('inf') or x == float('-inf') else x, return_dtype=pl.Float64).
↪clip(lower_bound=5.3).alias("predcoeff")
])

for col in final_test_df.columns:
    if final_test_df[col].dtype in [pl.Float64, pl.Float32, pl.Int64, pl.Int32,␣
↪pl.Int16, pl.Int8, pl.UInt64, pl.UInt32, pl.UInt16, pl.UInt8]:
        final_test_df = final_test_df.with_columns([
```

```
            pl.col(col).map_elements(lambda x: 0 if x == float('inf') or x ==␣
↪float('-inf') else x, return_dtype=pl.Float64)
        ])

for model in models:
    X_submission = final_test_df[feature_list + ["predcoeff"]].to_pandas()
    X_submission[cat_features] = X_submission[cat_features].astype("category")

    test_pred = model.predict(X_submission[feature_list]) *␣
↪X_submission["predcoeff"]
    test_preds.append(test_pred)

test_preds = np.mean(test_preds, axis=0)

preds_df = final_test_df.with_columns(pl.Series(test_preds).
↪alias("session_value"))
```

[19]:
```
out_df = sub.drop("session_value").join(preds_df.select("user_session",␣
↪"session_value"), on="user_session", how="left")

# Create a mapping from session_target_df for faster lookup
session_target_mapping = session_target_df.select("user_session",␣
↪"session_value")

# Join with the session target values and use coalesce to prioritize target␣
↪values
out_df = out_df.join(
    session_target_mapping.rename({"session_value": "target_session_value"}),
    on="user_session",
    how="left"
).with_columns(
    pl.coalesce("target_session_value", "session_value").alias("session_value")
).drop("target_session_value").with_columns(
    pl.col("session_value").clip(lower_bound=5.0)
)

out_df.write_csv("submission.csv")
```

1.11 9. Feature Importance

[20]:
```
f_imp = pd.DataFrame([model.estimators_[1].feature_name_,model.estimators_[0].
↪feature_importances_]).T
f_imp.columns = ["feature","importance"]
f_imp.sort_values("importance", ascending=False).head(50)
```

[20]:

	feature	importance
54	weighted_category_value_loo_view	907
29	sum_category_mean_value_loo_view	497
55	weighted_category_value_loo_add_cart	472
45	session_start_hour	363
28	session_positive_event_score	254
30	sum_category_mean_value_loo_add_cart	228
64	sum_session_positive_event_score	226
46	session_start_weekday	205
69	historical_mean_session_buy_count	165
81	historical_mean_session_depth	157
56	weighted_category_value_loo_remove_cart	148
5	session_duration_seconds	138
47	events_per_minute	131
79	category_diversity_ratio	125
87	sum_max_basket_coverage	118
77	session_duration_ratio	115
75	historical_session_count	114
76	session_length_ratio	109
83	historical_mean_session_end_efficiency	108
78	product_diversity_ratio	106
82	historical_mean_session_start_efficiency	96
65	historical_mean_session_event_count	95
31	sum_category_mean_value_loo_remove_cart	94
67	historical_mean_session_add_cart_count	85
66	historical_mean_session_view_count	80
23	goal_oriented_ratio	80
68	historical_mean_session_remove_cart_count	73
74	historical_cart_abandonment_rate	65
16	category_diversity	63
14	product_diversity	63
33	session_net_cart_count	59
11	unique_categories	58
22	cart_removal_rate	52
32	sum_category_mean_value_loo_buy	52
57	weighted_category_value_loo_buy	51
80	historical_mean_session_flow	47
84	historical_cart_engagement_rate	47
17	category_product_ratio	45
48	events_per_hour	43
71	historical_view_to_cart_ctr	42
49	session_duration_minutes	39
19	view_to_cart_rate	36
18	cart_to_purchase_rate	35
24	browsing_ratio	35
25	products_per_category	33
61	max_basket_coverage	31

51	session_end_efficiency	30
3	session_remove_cart_count	29
70	historical_view_to_buy_cr	29
72	historical_cart_to_buy_cr	28