# Sistem preporuka polovnih automobila zasnovan na Two-Tower arhitekturi

Cilj ovog projekta je izgradnja sistema za preporuku polovnih automobila koji uči zajednički embedding prostor za korisnike i vozila koristeći Two-Tower neuronsku arhitekturu. Model povezuje sintetičke korisničke preferencije i karakteristike automobila kako bi identifikovao najrelevantnije preporuke na osnovu njihove sličnosti.

In [43]:

```python
import re
import numpy as np
import pandas as pd

np.random.seed(42)

def extract_float(series: pd.Series) -> pd.Series:
    """
    Izvlaci prvi decimalni broj iz stringa (npr. '23.4 kmpl', '1248 CC')
    Ako nema broja, vraca NaN
    """
    s = series.astype(str)
    return pd.to_numeric(s.str.extract(r"(\d+\.?\d*)")[0], errors="coerce

def parse_torque_to_nm(torque_series: pd.Series) -> pd.Series:
    """
     Izvlaci vrednost obrtnog momenta, ako je u kgm/kg-m, konvertuje u Nm
    """
    raw = torque_series.astype(str)
    val = pd.to_numeric(raw.str.extract(r"(\d+\.?\d*)")[0], errors="coerc
    is_kgm = raw.str.contains(r"kgm|kg-m", case=False, na=False)
    val_nm = val.copy()
    val_nm.loc[is_kgm] = val_nm.loc[is_kgm] * 9.80665
    return val_nm

def extract_brand(name_series: pd.Series) -> pd.Series:
    """
    Brend je prva rec u nazivu automobila
    """
    s = name_series.astype(str).str.strip()
    return s.str.split().str[0].fillna("Unknown")


df = pd.read_csv("./car-details-v4.csv")
df.head()
```

Out[43]:

| | name | year | selling_price | km_driven | fuel | seller_type | transmission | own |
|---|---|---|---|---|---|---|---|---|
| **0** | Hyundai Grand i10 CRDi Asta Option | 2013 | 270000 | 118000 | Diesel | Individual | Manual | Fi Own |
| **1** | Hyundai Verna 1.6 SX | 2013 | 420000 | 69000 | Diesel | Individual | Manual | Thi Own |
| **2** | Maruti Swift Dzire LXI | 2015 | 434999 | 25000 | Petrol | Individual | Manual | Seco Own |
| **3** | Hyundai Xcent 1.2 Kappa AT S Option | 2015 | 400000 | 100000 | Petrol | Individual | Automatic | Fi Own |
| **4** | Maruti Swift Dzire VDI | 2015 | 470000 | 110000 | Diesel | Individual | Manual | Fi Own |

In [46]:

```python
df = df[
    [
        "name",
        "year",
        "selling_price",
        "km_driven",
        "fuel",
        "seller_type",
        "transmission",
        "owner",
        "mileage",
        "engine",
        "max_power",
        "torque",
        "seats",
    ]
].copy()
```

In [47]:

```python
df["mileage"] = extract_float(df["mileage"])
df["engine"] = extract_float(df["engine"])
df["max_power"] = extract_float(df["max_power"])
df["torque_nm"] = parse_torque_to_nm(df["torque"])
df["seats"] = pd.to_numeric(df["seats"], errors="coerce")

name = df["name"].astype(str)

df["body_coupe"] = name.str.contains(
    r"Coupe|Sports|Roadster|Convertible|Cabrio|Cabriolet|TT|Z4|S2000|Must
    case=False,
    na=False,
).astype(int)
```

```
df["body_sedan"] = name.str.contains(
    r"\bSedan\b|Dzire|City|Verna|Civic|Corolla|Passat|Octavia|Jetta|C-Cla
    case=False,
    na=False,
).astype(int)

df["body_suv"] = name.str.contains(
    r"Scorpio|Bolero|Fortuner|Safari|Innova|Jeep|XUV|Endeavour|Creta|Harr
    case=False,
    na=False,
).astype(int)

df["brand"] = extract_brand(df["name"])

premium_brands = {
    "Mercedes",
    "BMW",
    "Audi",
    "Lexus",
    "Jaguar",
    "Volvo",
    "Porsche",
    "Land",
    "Range",
}

df["is_premium_brand"] = df["brand"].isin(premium_brands).astype(int)
df.loc[name.str.contains(r"Land Rover", case=False, na=False), "is_premiu
df.loc[name.str.contains(r"Range Rover", case=False, na=False), "is_premi

cat_cols = ["fuel", "seller_type", "transmission", "owner"]
for c in cat_cols:
    df[c] = (
        df[c]
        .astype(str)
        .replace({"nan": np.nan, "None": np.nan})
        .fillna("Unknown")
        .str.strip()
    )

for c in ["year", "selling_price", "km_driven"]:
    df[c] = pd.to_numeric(df[c], errors="coerce")

df = df.dropna(subset=["name", "year", "selling_price", "km_driven"]).cop

num_cols = ["mileage", "engine", "max_power", "torque_nm", "seats"]

for c in num_cols:
    med = df[c].median()
    df[c] = df[c].fillna(med)

df = df[df["year"].between(1980, 2030)]
df = df[df["selling_price"] > 0]
df = df[df["km_driven"] >= 0]
df = df[df["seats"].between(2, 10)]

df.reset_index(drop=True, inplace=True)
df.head()
```

Out[47]:

| | name | year | selling_price | km_driven | fuel | seller_type | transmission | own |
|---|---|---|---|---|---|---|---|---|
| **0** | Hyundai Grand i10 CRDi Asta Option | 2013 | 270000 | 118000 | Diesel | Individual | Manual | Fi Own |
| **1** | Hyundai Verna 1.6 SX | 2013 | 420000 | 69000 | Diesel | Individual | Manual | Thi Own |
| **2** | Maruti Swift Dzire LXI | 2015 | 434999 | 25000 | Petrol | Individual | Manual | Seco Own |
| **3** | Hyundai Xcent 1.2 Kappa AT S Option | 2015 | 400000 | 100000 | Petrol | Individual | Automatic | Fi Own |
| **4** | Maruti Swift Dzire VDI | 2015 | 470000 | 110000 | Diesel | Individual | Manual | Fi Own |

In [48]:

```
df.describe()
```

Out[48]:

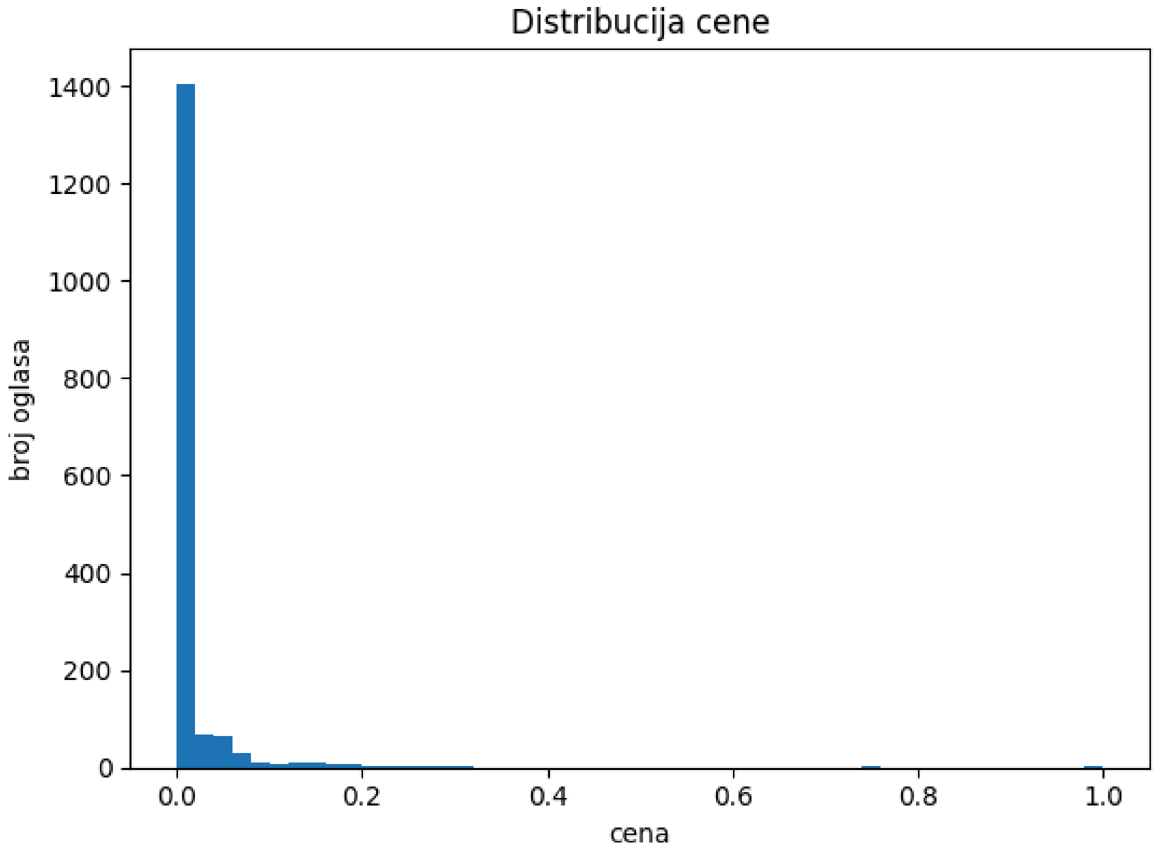
| | year | selling_price | km_driven | mileage | engine | ma |
|---|---|---|---|---|---|---|
| **count** | 1636.000000 | 1.636000e+03 | 1.636000e+03 | 1636.000000 | 1636.000000 | 163 |
| **mean** | 2014.342298 | 1.875745e+06 | 6.537767e+04 | 18.091589 | 1666.175428 | 13 |
| **std** | 4.453794 | 5.702215e+06 | 5.843320e+04 | 5.196142 | 945.871124 | 14 |
| **min** | 1995.000000 | 3.000000e+04 | 1.000000e+00 | 0.000000 | 0.000000 | ( |
| **25%** | 2012.000000 | 2.600000e+05 | 2.900000e+04 | 15.370000 | 1197.000000 | 7( |
| **50%** | 2015.000000 | 4.970000e+05 | 5.878850e+04 | 18.600000 | 1396.000000 | 8 |
| **75%** | 2018.000000 | 8.204992e+05 | 9.000000e+04 | 21.660000 | 1991.000000 | 12 |
| **max** | 2024.000000 | 1.250000e+08 | 1.500000e+06 | 32.520000 | 7011.000000 | 103 |

## EDA (Exploratory Data Analysis)

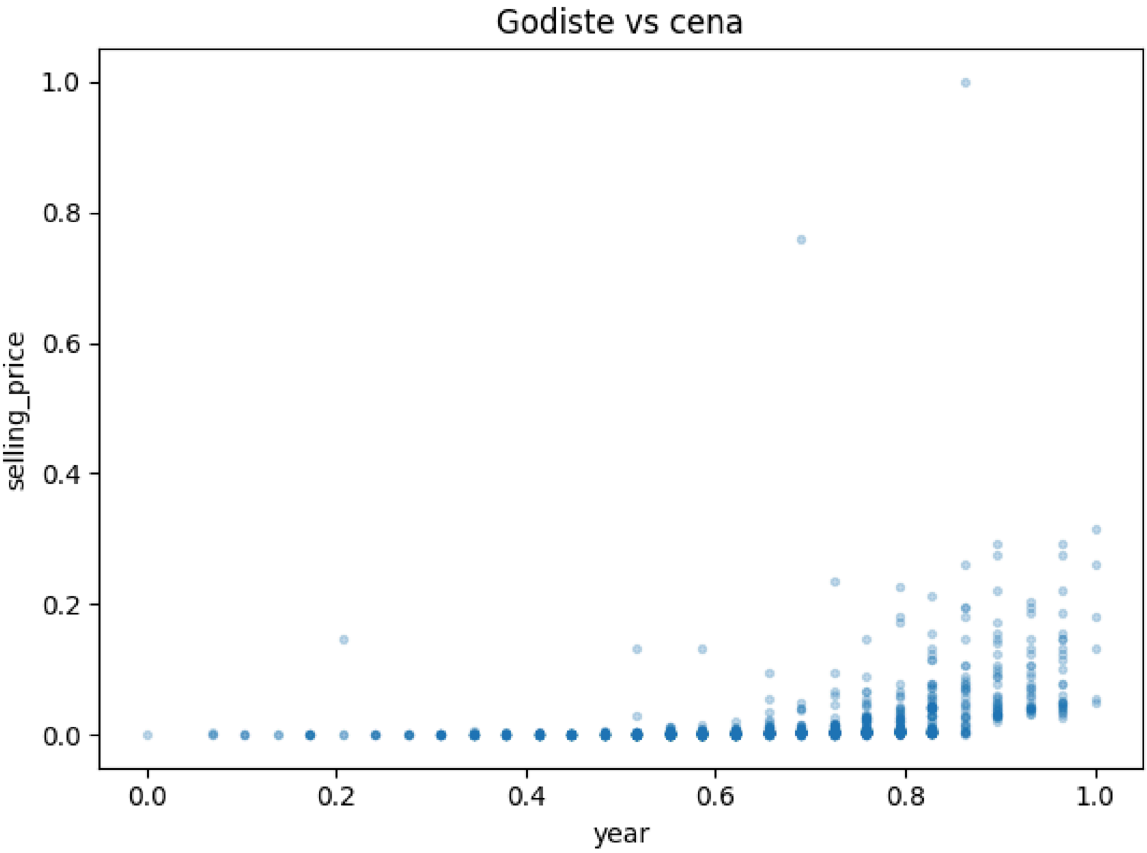
In [69]:

```
import matplotlib.pyplot as plt

plt.figure()
plt.hist(df["selling_price"].dropna(), bins=50)
plt.title("Distribucija cene")
plt.xlabel("cena")
plt.ylabel("broj oglasa")
plt.tight_layout()
plt.show()
```

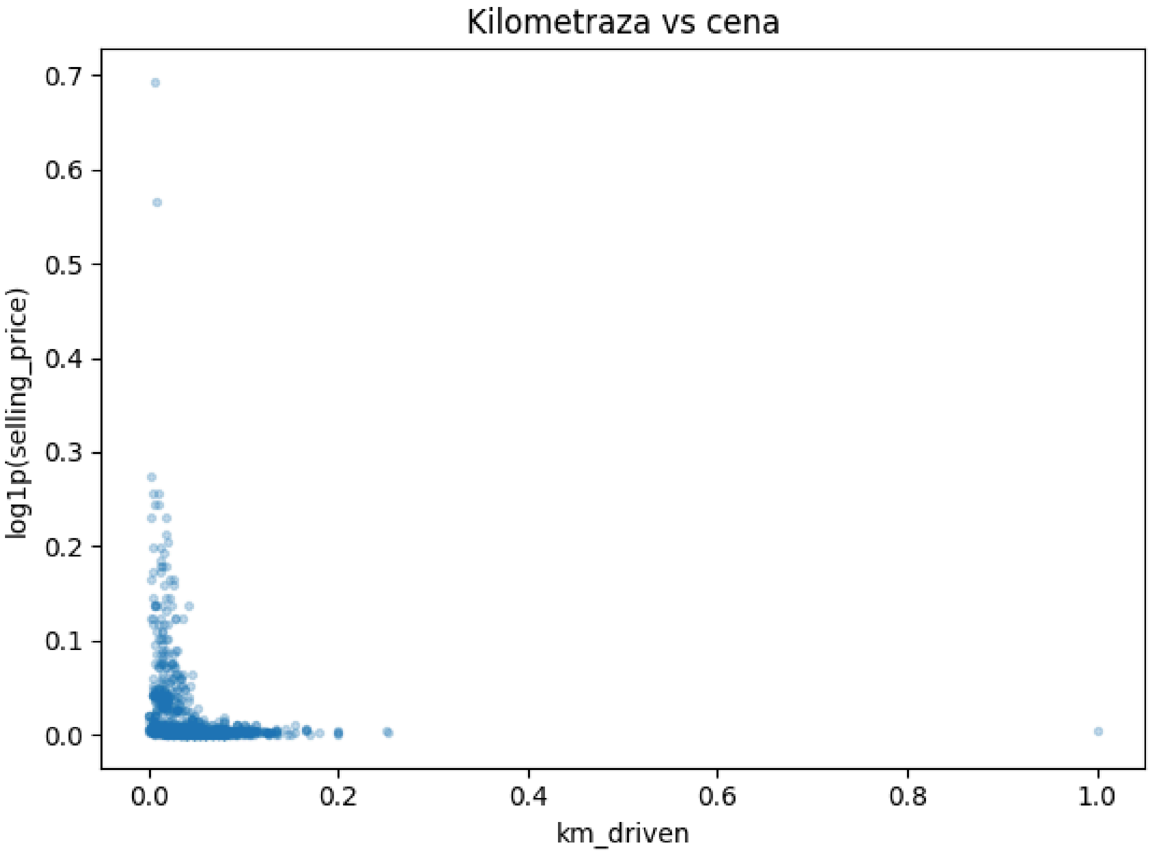


```
In [71]: plt.figure()
         plt.scatter(df["year"], df["selling_price"], s=8, alpha=0.25)
         plt.title("Godiste vs cena")
         plt.xlabel("year")
         plt.ylabel("selling_price")
         plt.tight_layout()
         plt.show()
```



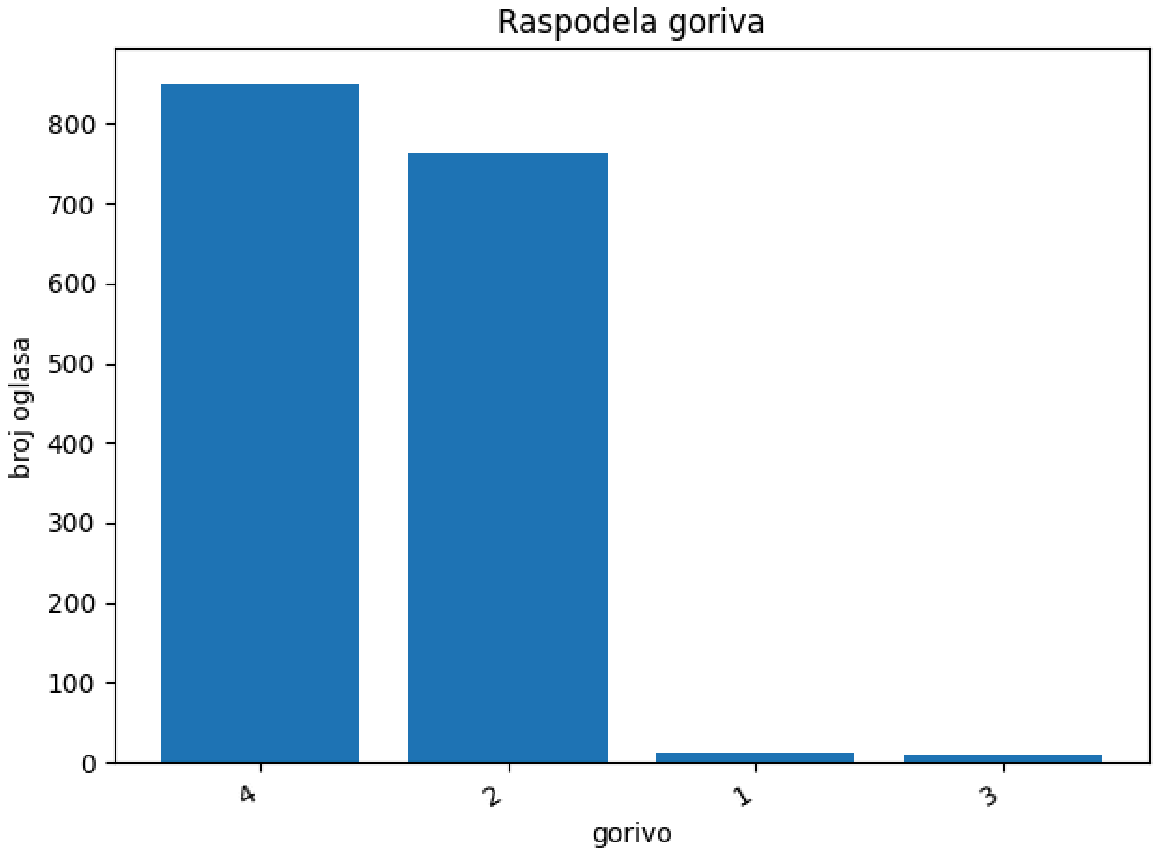
In [72]:

```
plt.figure()
plt.scatter(df["km_driven"], np.log1p(df["selling_price"]), s=8, alpha=0.
plt.title("Kilometraza vs cena")
plt.xlabel("km_driven")
plt.ylabel("log1p(selling_price)")
plt.tight_layout()
plt.show()
```



In [76]:

```
fuel_counts = df["fuel"].value_counts(dropna=False)
plt.figure()
plt.bar(fuel_counts.index.astype(str), fuel_counts.values)
plt.title("Raspodela goriva")
plt.xlabel("gorivo")
plt.ylabel("broj oglasa")
plt.xticks(rotation=30, ha="right")
plt.tight_layout()
plt.show()
```



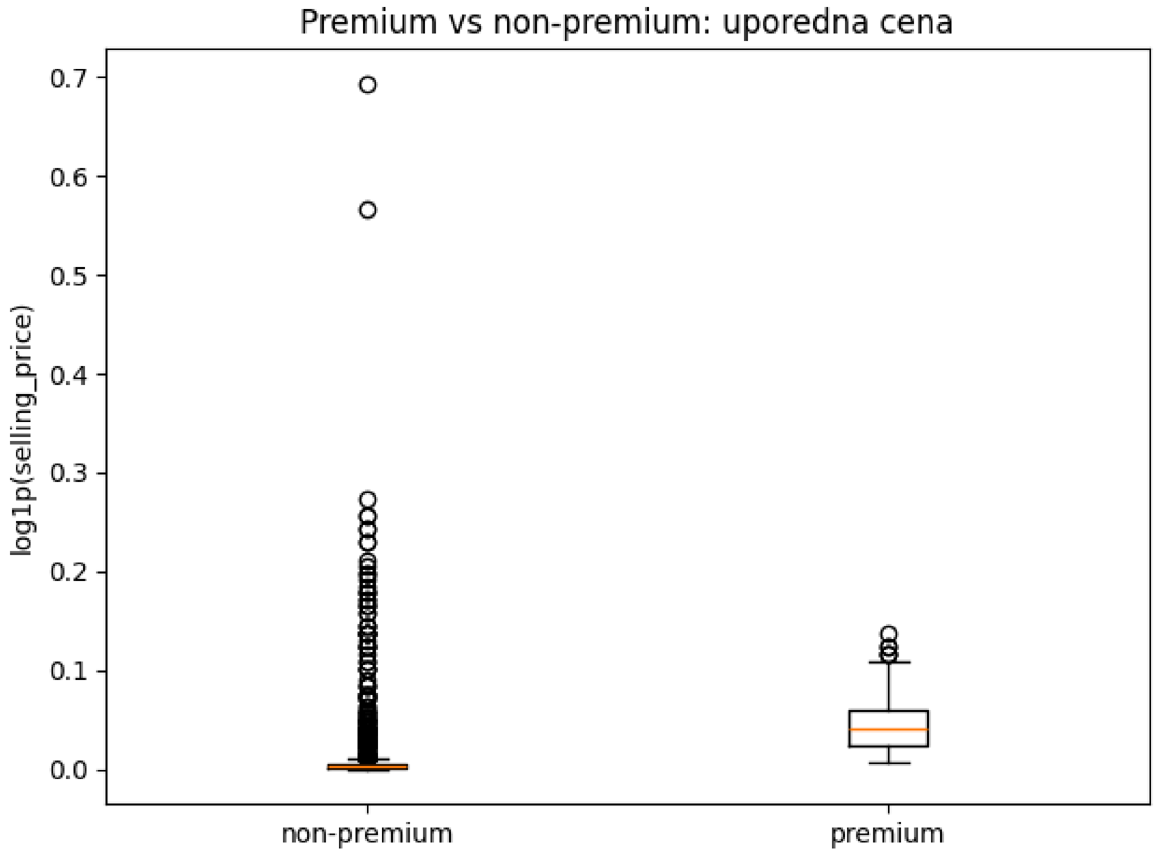
1. Metan (CNG)
2. Dizel
3. Plin (LPG)
4. Benzin

In [78]:

```
premium = np.log1p(df.loc[df["is_premium_brand"] == 1, "selling_price"])
non_premium = np.log1p(df.loc[df["is_premium_brand"] == 0, "selling_price

plt.figure()
plt.boxplot([non_premium.dropna(), premium.dropna()], labels=["non-premiu
plt.title("Premium vs non-premium: uporedna cena")
plt.ylabel("log1p(selling_price)")
plt.tight_layout()
plt.show()
```

```
/var/folders/1z/y0431qm13ys1l9h5w9tslfgw0000gn/T/ipykernel_58114/392467044
2.py:5: MatplotlibDeprecationWarning: The 'labels' parameter of boxplot()
has been renamed 'tick_labels' since Matplotlib 3.9; support for the old n
ame will be dropped in 3.11.
  plt.boxplot([non_premium.dropna(), premium.dropna()], labels=["non-premi
um", "premium"])
```



## Preprocesiranje/Enkodiranje

In [80]:

```
from sklearn.preprocessing import MinMaxScaler

NUM_COLS = [
    "year",
    "selling_price",
    "km_driven",
    "mileage",
    "engine",
    "max_power",
    "torque_nm",
    "seats",
]

CAT_COLS = ["fuel", "seller_type", "transmission", "owner"]
BIN_COLS = ["body_suv", "body_sedan", "body_coupe", "is_premium_brand"]

for c in CAT_COLS:
    df[c] = df[c].fillna("Unknown").astype(str).str.strip()

scaler = MinMaxScaler()
df[NUM_COLS] = scaler.fit_transform(df[NUM_COLS])

cat_maps = {}
cat_sizes = {}

for c in CAT_COLS:
    cats = pd.Index(sorted(df[c].unique()))
    if "Unknown" not in cats:
        cats = pd.Index(["Unknown"]).append(cats)
    cat_maps[c] = {k: i for i, k in enumerate(cats)}
```

```
        cat_sizes[c] = len(cats)
        df[c] = df[c].map(cat_maps[c]).fillna(cat_maps[c]["Unknown"]).astype(

    num_fuel = cat_sizes["fuel"]
    num_seller = cat_sizes["seller_type"]
    num_trans = cat_sizes["transmission"]
    num_owner = cat_sizes["owner"]

    def get_code(col: str, name: str) -> int:
        return cat_maps[col].get(name, cat_maps[col]["Unknown"])

    petrol_code = get_code("fuel", "Petrol")
    diesel_code = get_code("fuel", "Diesel")

    manual_code = get_code("transmission", "Manual")
    auto_code = get_code("transmission", "Automatic")

    first_owner_code = get_code("owner", "First Owner")

    df_items = df[NUM_COLS + CAT_COLS + BIN_COLS].copy()
    df_items.head()
```

Out[80]:

| | year | selling_price | km_driven | mileage | engine | max_power | torque_nn |
|---|---|---|---|---|---|---|---|
| **0** | 0.620690 | 0.001920 | 0.078666 | 0.738007 | 0.159749 | 0.067633 | 0.08104 |
| **1** | 0.620690 | 0.003121 | 0.045999 | 0.686347 | 0.225645 | 0.122048 | 0.15325 |
| **2** | 0.689655 | 0.003241 | 0.016666 | 0.641144 | 0.170732 | 0.080329 | 0.04848 |
| **3** | 0.689655 | 0.002961 | 0.066666 | 0.519680 | 0.170732 | 0.079092 | 0.04757 |
| **4** | 0.689655 | 0.003521 | 0.073333 | 0.817651 | 0.178006 | 0.071498 | 0.10275 |

In [81]:

```
df_items.isna().sum()
```

Out[81]:

```
year                0
selling_price       0
km_driven           0
mileage             0
engine              0
max_power           0
torque_nm           0
seats               0
fuel                0
seller_type         0
transmission        0
owner               0
body_suv            0
body_sedan          0
body_coupe          0
is_premium_brand    0
dtype: int64
```

## Generisanje korisnika po segmentima

In [84]:

```
def generate_segment_users(n_per_segment=40):
    users = []
    for _ in range(n_per_segment):

        # 1) Ograniceni budzet (niske cene auta, mala snaga, mala potrosn
        users.append({
            "year": np.random.uniform(0.25, 0.55),
            "selling_price": np.random.uniform(0.10, 0.35),
            "km_driven": np.random.uniform(0.30, 0.80),
            "mileage": np.random.uniform(0.60, 1.00),
            "engine": np.random.uniform(0.20, 0.50),
            "max_power": np.random.uniform(0.20, 0.50),
            "torque_nm": np.random.uniform(0.20, 0.50),
            "seats": np.random.uniform(0.30, 0.70),
            "fuel": petrol_code,
            "seller_type": get_code("seller_type", "Individual"),
            "transmission": manual_code,
            "owner": first_owner_code,
            "body_suv": 0,
            "body_sedan": 1,
            "body_coupe": 0,
            "is_premium_brand": 0,
            "segment": 1,
        })

        # 2) Dizel putnik (duza putovanja, pouzdani motori...)
        users.append({
            "year": np.random.uniform(0.45, 0.80),
            "selling_price": np.random.uniform(0.30, 0.60),
            "km_driven": np.random.uniform(0.20, 0.60),
            "mileage": np.random.uniform(0.50, 0.90),
            "engine": np.random.uniform(0.40, 0.70),
            "max_power": np.random.uniform(0.30, 0.60),
            "torque_nm": np.random.uniform(0.40, 0.80),
            "seats": np.random.uniform(0.40, 0.70),
            "fuel": diesel_code,
            "seller_type": get_code("seller_type", "Dealer"),
            "transmission": manual_code,
            "owner": first_owner_code,
            "body_suv": 0,
            "body_sedan": 1,
            "body_coupe": 0,
            "is_premium_brand": 0,
            "segment": 2,
        })

        # 3) Porodicni kupac (vise prostora, bolja sigurnost...)
        users.append({
            "year": np.random.uniform(0.60, 0.90),
            "selling_price": np.random.uniform(0.40, 0.70),
            "km_driven": np.random.uniform(0.10, 0.40),
            "mileage": np.random.uniform(0.40, 0.80),
            "engine": np.random.uniform(0.40, 0.70),
            "max_power": np.random.uniform(0.40, 0.70),
            "torque_nm": np.random.uniform(0.40, 0.70),
            "seats": np.random.uniform(0.60, 1.00),
            "fuel": np.random.choice([petrol_code, diesel_code]),
            "seller_type": get_code("seller_type", "Dealer"),
            "transmission": auto_code,
            "owner": first_owner_code,
            "body_suv": 1,
            "body_sedan": 0,
            "body_coupe": 0,
            "is_premium_brand": 0,
            "segment": 3,
        })

        # 4) Sportski entuzijasta (bolje performanse, manji broj sedista.
        users.append({
            "year": np.random.uniform(0.55, 0.95),
            "selling_price": np.random.uniform(0.60, 0.95),
            "km_driven": np.random.uniform(0.03, 0.25),
            "mileage": np.random.uniform(0.30, 0.70),
            "engine": np.random.uniform(0.55, 0.85),
            "max_power": np.random.uniform(0.80, 1.00),
            "torque_nm": np.random.uniform(0.65, 1.00),
            "seats": np.random.uniform(0.10, 0.35),
            "fuel": petrol_code,
            "seller_type": np.random.choice([
                get_code("seller_type", "Individual"),
                get_code("seller_type", "Dealer"),
            ]),
            "transmission": manual_code,
            "owner": first_owner_code,
            "body_suv": 0,
            "body_sedan": 0,
            "body_coupe": 1,
            "is_premium_brand": 0,
            "segment": 4,
        })

    return pd.DataFrame(users)


users_df = generate_segment_users(40)
users_df.head()
```

Out[84]:

|   | year | selling_price | km_driven | mileage | engine | max_power | torque_nr |
|---|---|---|---|---|---|---|---|
| **0** | 0.333409 | 0.306482 | 0.679816 | 0.784262 | 0.387316 | 0.232405 | 0.29576 |
| **1** | 0.579905 | 0.308078 | 0.402065 | 0.531320 | 0.683146 | 0.437538 | 0.78098 |
| **2** | 0.727169 | 0.412312 | 0.141442 | 0.577608 | 0.492983 | 0.506988 | 0.67128 |
| **3** | 0.914978 | 0.809056 | 0.137083 | 0.347656 | 0.568169 | 0.827266 | 0.81274 |
| **4** | 0.416409 | 0.274233 | 0.331824 | 0.761082 | 0.255868 | 0.315171 | 0.22289 |

## Bodovanje automobila po segmentima

In [51]:

```
def score_items_for_segment(user_row, cars_df: pd.DataFrame):
    seg = int(user_row["segment"])
    cars = cars_df
    n = len(cars)

    user_num = user_row[NUM_COLS].values.astype("float32")
    car_num = cars[NUM_COLS].values.astype("float32")

    diff = np.abs(car_num - user_num)
    base_sim = np.clip(1.0 - diff, 0.0, 1.0)
    base_score = base_sim.sum(axis=1).astype("float32")

    fuel = cars["fuel"].values
    seller = cars["seller_type"].values
    trans = cars["transmission"].values
    owner = cars["owner"].values

    year = cars["year"].values
    price = cars["selling_price"].values
    km = cars["km_driven"].values
    mileage = cars["mileage"].values
    engine = cars["engine"].values
    power = cars["max_power"].values
    torque_nm = cars["torque_nm"].values
    seats = cars["seats"].values

    body_suv = cars["body_suv"].values.astype("float32")
    body_sedan = cars["body_sedan"].values.astype("float32")
    body_coupe = cars["body_coupe"].values.astype("float32")
    is_premium = cars["is_premium_brand"].values.astype("float32")

    score = base_score.copy()

    if seg == 1:
        score += 2.0 * (1 - np.abs(price - user_row["selling_price"]))
        score += 1.0 * (1 - np.abs(mileage - user_row["mileage"]))
        score += 0.8 * (fuel == user_row["fuel"])
        score += 0.5 * (seller == user_row["seller_type"])
        score += 0.3 * (owner == user_row["owner"])

    elif seg == 2:
        score += 2.5 * (fuel == diesel_code)
        score += 1.5 * (1 - np.abs(mileage - user_row["mileage"]))
        score += 0.8 * (trans == manual_code)
        score -= 0.8 * body_suv

    elif seg == 3:
        score += 1.5 * (seats >= 0.6).astype("float32")
        score += 0.8 * (trans == auto_code)
        score += 0.5 * body_suv

    elif seg == 4:
        score += 2.0 * power
        score += 1.0 * engine
        score += 1.0 * torque_nm
        score += 2.0 * body_coupe
        score -= 1.5 * body_suv
        score -= 0.8 * body_sedan
        score += 0.8 * (trans == manual_code)
        score += 0.5 * (fuel == petrol_code)
        score += 0.8 * (seats <= 0.5).astype("float32")

    return score.astype("float32")
```

## Generisanje trening parova (pozitivni/negativni)

In [52]:

```
def generate_training_pairs(users_df, cars_df, n_pos=15, n_neg=15, hard_n
    cars_num = cars_df[NUM_COLS].values.astype("float32")
    cars_fuel = cars_df["fuel"].values.astype("int32")
    cars_seller = cars_df["seller_type"].values.astype("int32")
    cars_trans = cars_df["transmission"].values.astype("int32")
    cars_owner = cars_df["owner"].values.astype("int32")
    cars_bin = cars_df[BIN_COLS].values.astype("float32")

    u_num_list, u_fuel_list, u_seller_list, u_trans_list, u_owner_list, u
    i_num_list, i_fuel_list, i_seller_list, i_trans_list, i_owner_list, i
    y_list = []

    n_items = len(cars_df)
    n_hard = int(n_neg * hard_neg_ratio)
    n_rand = n_neg - n_hard

    for _, user in users_df.iterrows():
        scores = score_items_for_segment(user, cars_df)
        idx_sorted = np.argsort(scores)

        pos_idx = idx_sorted[-n_pos:]

        hard_pool = idx_sorted[-(n_pos + 200):-n_pos] if n_items > (n_pos
        if len(hard_pool) == 0:
            hard_pool = idx_sorted[: max(1, n_items - n_pos)]

        hard_idx = (
            np.random.choice(hard_pool, size=min(n_hard, len(hard_pool)),
            if n_hard > 0
            else np.array([], dtype=int)
        )

        rand_pool = np.setdiff1d(np.arange(n_items), pos_idx, assume_uniq
        rand_idx = (
            np.random.choice(rand_pool, size=min(n_rand, len(rand_pool)),
            if n_rand > 0
            else np.array([], dtype=int)
        )

        neg_idx = np.concatenate([hard_idx, rand_idx])

        u_num = user[NUM_COLS].values.astype("float32")
        u_fuel = int(user["fuel"])
        u_seller = int(user["seller_type"])
        u_trans = int(user["transmission"])
        u_owner = int(user["owner"])
        u_bin = user[BIN_COLS].values.astype("float32")

        def add(indices, label):
            for idx in indices:
                u_num_list.append(u_num)
                u_fuel_list.append(u_fuel)
                u_seller_list.append(u_seller)
                u_trans_list.append(u_trans)
                u_owner_list.append(u_owner)
                u_bin_list.append(u_bin)

                i_num_list.append(cars_num[idx])
                i_fuel_list.append(int(cars_fuel[idx]))
                i_seller_list.append(int(cars_seller[idx]))
                i_trans_list.append(int(cars_trans[idx]))
                i_owner_list.append(int(cars_owner[idx]))
                i_bin_list.append(cars_bin[idx])
                y_list.append(float(label))

        add(pos_idx, 1.0)
        add(neg_idx, 0.0)

    return (
        np.stack(u_num_list).astype("float32"),
        np.array(u_fuel_list, dtype="int32"),
        np.array(u_seller_list, dtype="int32"),
        np.array(u_trans_list, dtype="int32"),
        np.array(u_owner_list, dtype="int32"),
        np.stack(u_bin_list).astype("float32"),
        np.stack(i_num_list).astype("float32"),
        np.array(i_fuel_list, dtype="int32"),
        np.array(i_seller_list, dtype="int32"),
        np.array(i_trans_list, dtype="int32"),
        np.array(i_owner_list, dtype="int32"),
        np.stack(i_bin_list).astype("float32"),
        np.array(y_list, dtype="float32"),
    )
```

## User & Item tornjevi

In [86]:

```
import tensorflow as tf
from tensorflow.keras import layers, Model

embedding_dim = 32
num_numeric = len(NUM_COLS)
num_bin = len(BIN_COLS)

def emb_dim(n):
    return int(min(16, max(4, round(np.sqrt(n)))))

fuel_emb_dim = emb_dim(num_fuel)
seller_emb_dim = emb_dim(num_seller)
trans_emb_dim = emb_dim(num_trans)
owner_emb_dim = emb_dim(num_owner)

# USER tower
user_numeric_in = layers.Input(shape=(num_numeric,), name="user_num")
user_bin_in = layers.Input(shape=(num_bin,), name="user_bin")

user_fuel_in = layers.Input(shape=(), dtype="int32", name="user_fuel")
user_seller_in = layers.Input(shape=(), dtype="int32", name="user_seller"
user_trans_in = layers.Input(shape=(), dtype="int32", name="user_trans")
user_owner_in = layers.Input(shape=(), dtype="int32", name="user_owner")

uf_emb = layers.Embedding(num_fuel, fuel_emb_dim)(user_fuel_in)
us_emb = layers.Embedding(num_seller, seller_emb_dim)(user_seller_in)
ut_emb = layers.Embedding(num_trans, trans_emb_dim)(user_trans_in)
uo_emb = layers.Embedding(num_owner, owner_emb_dim)(user_owner_in)

u_concat = layers.Concatenate()([
    user_numeric_in,
    user_bin_in,
    layers.Reshape((fuel_emb_dim,))(uf_emb),
    layers.Reshape((seller_emb_dim,))(us_emb),
    layers.Reshape((trans_emb_dim,))(ut_emb),
    layers.Reshape((owner_emb_dim,))(uo_emb),
])

u_hidden = layers.Dense(128, activation="relu")(u_concat)
u_hidden = layers.Dropout(0.2)(u_hidden)
u_hidden = layers.Dense(64, activation="relu")(u_hidden)
u_vec = layers.Dense(embedding_dim)(u_hidden)
u_vec = layers.Lambda(lambda x: tf.nn.l2_normalize(x, axis=1), name="user

user_tower = Model(
    inputs=[user_numeric_in, user_bin_in, user_fuel_in, user_seller_in, u
    outputs=u_vec,
    name="user_tower",
)

# ITEM tower
item_numeric_in = layers.Input(shape=(num_numeric,), name="item_num")
item_bin_in = layers.Input(shape=(num_bin,), name="item_bin")

item_fuel_in = layers.Input(shape=(), dtype="int32", name="item_fuel")
item_seller_in = layers.Input(shape=(), dtype="int32", name="item_seller"
item_trans_in = layers.Input(shape=(), dtype="int32", name="item_trans")
item_owner_in = layers.Input(shape=(), dtype="int32", name="item_owner")

if_emb = layers.Embedding(num_fuel, fuel_emb_dim)(item_fuel_in)
is_emb = layers.Embedding(num_seller, seller_emb_dim)(item_seller_in)
it_emb = layers.Embedding(num_trans, trans_emb_dim)(item_trans_in)
io_emb = layers.Embedding(num_owner, owner_emb_dim)(item_owner_in)

i_concat = layers.Concatenate()([
    item_numeric_in,
    item_bin_in,
    layers.Reshape((fuel_emb_dim,))(if_emb),
    layers.Reshape((seller_emb_dim,))(is_emb),
    layers.Reshape((trans_emb_dim,))(it_emb),
    layers.Reshape((owner_emb_dim,))(io_emb),
])

i_hidden = layers.Dense(128, activation="relu")(i_concat)
i_hidden = layers.Dropout(0.2)(i_hidden)
i_hidden = layers.Dense(64, activation="relu")(i_hidden)
i_vec = layers.Dense(embedding_dim)(i_hidden)
i_vec = layers.Lambda(lambda x: tf.nn.l2_normalize(x, axis=1), name="item

item_tower = Model(
    inputs=[item_numeric_in, item_bin_in, item_fuel_in, item_seller_in, i
    outputs=i_vec,
    name="item_tower",
)
```

## Two Tower model

In [87]:

```
dot_score = layers.Dot(axes=1, name="dot")([u_vec, i_vec])

model = Model(
    inputs=[
        user_numeric_in, user_bin_in, user_fuel_in, user_seller_in, user_
        item_numeric_in, item_bin_in, item_fuel_in, item_seller_in, item_
    ],
    outputs=dot_score,
    name="two_tower",
)

model.compile(
    optimizer=tf.keras.optimizers.Adam(1e-3),
    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
)

model.summary()
```

```
Model: "two_tower"
```

```
┏━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━┳━━━━━━━━━━━
┃ Layer (type)        ┃ Output Shape      ┃    Param # ┃ Connected t
┡━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━╇━━━━━━━━━━━
│ user_fuel           │ (None)            │          0 │ -
│ (InputLayer)        │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ user_seller         │ (None)            │          0 │ -
│ (InputLayer)        │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ user_trans          │ (None)            │          0 │ -
│ (InputLayer)        │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ user_owner          │ (None)            │          0 │ -
│ (InputLayer)        │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ item_fuel           │ (None)            │          0 │ -
│ (InputLayer)        │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ item_seller         │ (None)            │          0 │ -
│ (InputLayer)        │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ item_trans          │ (None)            │          0 │ -
│ (InputLayer)        │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ item_owner          │ (None)            │          0 │ -
│ (InputLayer)        │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ embedding_24        │ (None, 4)         │         20 │ user_fuel[
│ (Embedding)         │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ embedding_25        │ (None, 4)         │         16 │ user_selle
│ (Embedding)         │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ embedding_26        │ (None, 4)         │         12 │ user_trans
│ (Embedding)         │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ embedding_27        │ (None, 4)         │         20 │ user_owner
│ (Embedding)         │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ embedding_28        │ (None, 4)         │         20 │ item_fuel[
│ (Embedding)         │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ embedding_29        │ (None, 4)         │         16 │ item_selle
│ (Embedding)         │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ embedding_30        │ (None, 4)         │         12 │ item_trans
│ (Embedding)         │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ embedding_31        │ (None, 4)         │         20 │ item_owner
│ (Embedding)         │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ user_num            │ (None, 8)         │          0 │ -
│ (InputLayer)        │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ user_bin            │ (None, 4)         │          0 │ -
│ (InputLayer)        │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ reshape_24          │ (None, 4)         │          0 │ embedding_
│ (Reshape)           │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ reshape_25          │ (None, 4)         │          0 │ embedding_
│ (Reshape)           │                   │            │
├─────────────────────┼───────────────────┼────────────┼───────────
│ reshape_26          │ (None, 4)         │          0 │ embedding_
│ (Reshape)            │                   │            │             
├──────────────────────┼───────────────────┼────────────┼─────────────
│ reshape_27           │ (None, 4)         │          0 │ embedding_
│ (Reshape)            │                   │            │             
├──────────────────────┼───────────────────┼────────────┼─────────────
│ item_num             │ (None, 8)         │          0 │ -           
│ (InputLayer)         │                   │            │             
├──────────────────────┼───────────────────┼────────────┼─────────────
│ item_bin             │ (None, 4)         │          0 │ -           
│ (InputLayer)         │                   │            │             
├──────────────────────┼───────────────────┼────────────┼─────────────
│ reshape_28           │ (None, 4)         │          0 │ embedding_
│ (Reshape)            │                   │            │             
├──────────────────────┼───────────────────┼────────────┼─────────────
│ reshape_29           │ (None, 4)         │          0 │ embedding_
│ (Reshape)            │                   │            │             
├──────────────────────┼───────────────────┼────────────┼─────────────
│ reshape_30           │ (None, 4)         │          0 │ embedding_
│ (Reshape)            │                   │            │             
├──────────────────────┼───────────────────┼────────────┼─────────────
│ reshape_31           │ (None, 4)         │          0 │ embedding_
│ (Reshape)            │                   │            │             
├──────────────────────┼───────────────────┼────────────┼─────────────
│ concatenate_6        │ (None, 28)        │          0 │ user_num[0
│ (Concatenate)        │                   │            │ user_bin[0
│                      │                   │            │ reshape_24
│                      │                   │            │ reshape_25
│                      │                   │            │ reshape_26
│                      │                   │            │ reshape_27
├──────────────────────┼───────────────────┼────────────┼─────────────
│ concatenate_7        │ (None, 28)        │          0 │ item_num[0
│ (Concatenate)        │                   │            │ item_bin[0
│                      │                   │            │ reshape_28
│                      │                   │            │ reshape_29
│                      │                   │            │ reshape_30
│                      │                   │            │ reshape_31
├──────────────────────┼───────────────────┼────────────┼─────────────
│ dense_18 (Dense)     │ (None, 128)       │      3,712 │ concatenat
├──────────────────────┼───────────────────┼────────────┼─────────────
│ dense_21 (Dense)     │ (None, 128)       │      3,712 │ concatenat
├──────────────────────┼───────────────────┼────────────┼─────────────
│ dropout_6 (Dropout)  │ (None, 128)       │          0 │ dense_18[0
├──────────────────────┼───────────────────┼────────────┼─────────────
│ dropout_7 (Dropout)  │ (None, 128)       │          0 │ dense_21[0
├──────────────────────┼───────────────────┼────────────┼─────────────
│ dense_19 (Dense)     │ (None, 64)        │      8,256 │ dropout_6[
├──────────────────────┼───────────────────┼────────────┼─────────────
│ dense_22 (Dense)     │ (None, 64)        │      8,256 │ dropout_7[
├──────────────────────┼───────────────────┼────────────┼─────────────
│ dense_20 (Dense)     │ (None, 32)        │      2,080 │ dense_19[0
├──────────────────────┼───────────────────┼────────────┼─────────────
│ dense_23 (Dense)     │ (None, 32)        │      2,080 │ dense_22[0
├──────────────────────┼───────────────────┼────────────┼─────────────
│ user_l2 (Lambda)     │ (None, 32)        │          0 │ dense_20[0
├──────────────────────┼───────────────────┼────────────┼─────────────
│ item_l2 (Lambda)     │ (None, 32)        │          0 │ dense_23[0
├──────────────────────┼───────────────────┼────────────┼─────────────
│ dot (Dot)            │ (None, 1)         │          0 │ user_l2[0]
│                      │                   │            │ item_l2[0]
└──────────────────────┴───────────────────┴────────────┴─────────────
 Total params: 28,232 (110.28 KB)
 Trainable params: 28,232 (110.28 KB)
```

```
Non-trainable params: 0 (0.00 B)
```

In [88]:

```
(
    u_num,
    u_fuel,
    u_seller,
    u_trans,
    u_owner,
    u_bin,
    i_num,
    i_fuel,
    i_seller,
    i_trans,
    i_owner,
    i_bin,
    y,
) = generate_training_pairs(users_df, df_items, n_pos=15, n_neg=15, hard_

history = model.fit(
    [
        u_num, u_bin, u_fuel, u_seller, u_trans, u_owner,
        i_num, i_bin, i_fuel, i_seller, i_trans, i_owner,
    ],
    y,
    epochs=10,
    batch_size=64,
    verbose=1,
)

def build_item_inputs_from_df(cars_df: pd.DataFrame):
    num = cars_df[NUM_COLS].values.astype("float32")
    bin_ = cars_df[BIN_COLS].values.astype("float32")
    fuel = cars_df["fuel"].values.astype("int32")
    seller = cars_df["seller_type"].values.astype("int32")
    trans = cars_df["transmission"].values.astype("int32")
    owner = cars_df["owner"].values.astype("int32")
    return num, bin_, fuel, seller, trans, owner

item_num_all, item_bin_all, item_fuel_all, item_seller_all, item_trans_al

item_embeddings = item_tower.predict(
    [item_num_all, item_bin_all, item_fuel_all, item_seller_all, item_tra
    verbose=0,
)
```

```
Epoch 1/10
75/75 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - loss: 0.6060
Epoch 2/10
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.5446
Epoch 3/10
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.5244
Epoch 4/10
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.5041
Epoch 5/10
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.4910
Epoch 6/10
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.4809
Epoch 7/10
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.4735
Epoch 8/10
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.4678
Epoch 9/10
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.4654
Epoch 10/10
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.4602
```

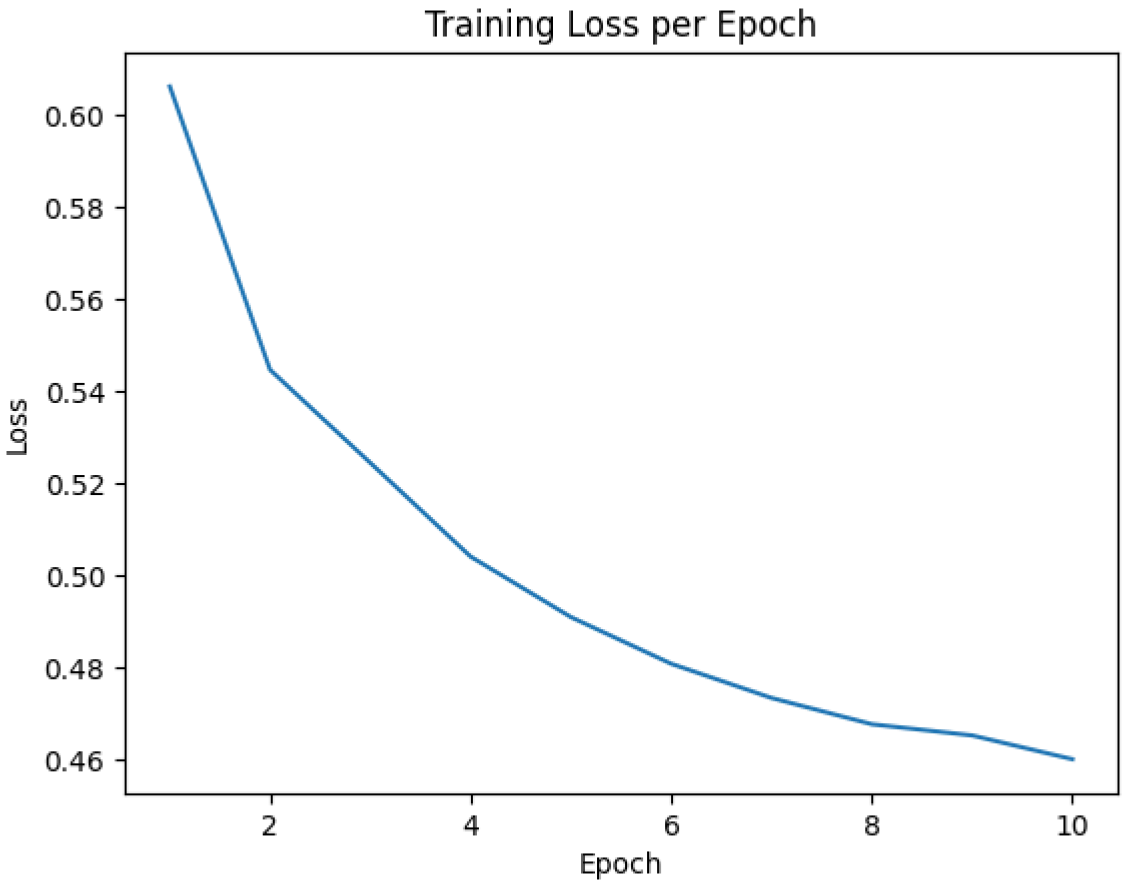
Vidimo da loss pada iz epohe u epohu, sto znaci da model uci i da je stabilan.

In [89]:

```python
import matplotlib.pyplot as plt

loss = history.history["loss"]
epochs = range(1, len(loss) + 1)

plt.figure()
plt.plot(epochs, loss)
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Training Loss per Epoch")
plt.show()
```



## Skorovi za trening parove

In [119…

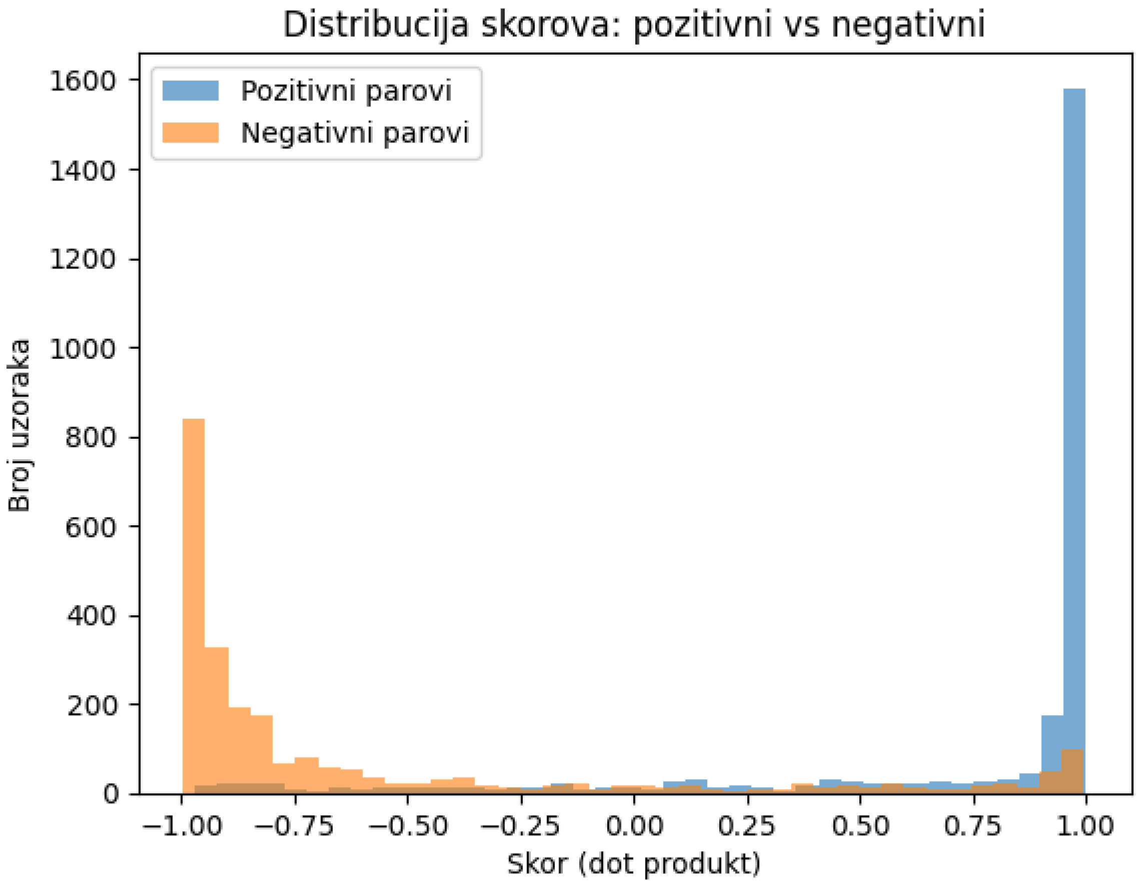
```
u_emb_train = user_tower.predict(
    [u_num, u_bin, u_fuel, u_seller, u_trans, u_owner],
    verbose=0,
)
i_emb_train = item_tower.predict(
    [i_num, i_bin, i_fuel, i_seller, i_trans, i_owner],
    verbose=0,
)

train_scores = np.sum(u_emb_train * i_emb_train, axis=1)

# podela po labeli
pos_scores = train_scores[y == 1]
neg_scores = train_scores[y == 0]

# graf
import matplotlib.pyplot as plt

plt.figure()
plt.hist(pos_scores, bins=40, alpha=0.6, label="Pozitivni parovi")
plt.hist(neg_scores, bins=40, alpha=0.6, label="Negativni parovi")
plt.xlabel("Skor (dot produkt)")
plt.ylabel("Broj uzoraka")
plt.legend()
plt.title("Distribucija skorova: pozitivni vs negativni")
plt.show()
```



Vidimo jasno razdvajanje skorova pozitivnih i negativnih parova.

In [113…

```
def recommend_for_user(user_pref: dict, top_n=10):
    user_num = np.array([[user_pref[c] for c in NUM_COLS]], dtype="float3
    user_bin = np.array([[user_pref[c] for c in BIN_COLS]], dtype="float3

    user_fuel = np.array([user_pref["fuel"]], dtype="int32")
    user_seller = np.array([user_pref["seller_type"]], dtype="int32")
    user_trans = np.array([user_pref["transmission"]], dtype="int32")
    user_owner = np.array([user_pref["owner"]], dtype="int32")

    u_emb = user_tower.predict(
        [user_num, user_bin, user_fuel, user_seller, user_trans, user_own
        verbose=0,
    )

    scores = (u_emb @ item_embeddings.T).ravel()
    sorted_idx = np.argsort(scores)[::-1]

    seen_names = set()
    selected_idx = []
    selected_scores = []

    for idx in sorted_idx:
        name = df.iloc[idx]["name"]
        if name not in seen_names:
            seen_names.add(name)
            selected_idx.append(idx)
            selected_scores.append(float(scores[idx]))
        if len(selected_idx) == top_n:
            break
    out = df.iloc[selected_idx][
        ["name", "year", "selling_price", "km_driven", "fuel", "transmiss
    ].copy()
    return out
```

## Test

In [114…

```
SEGMENT_NAMES = {
    1: "Sport",
    2: "Budzet",
    3: "Porodica",
    4: "Dizel",
}

def make_user_pref(segment: int) -> dict:
    if segment == 1:  # Sport
        return {
            "year": 0.80,
            "selling_price": 0.85,
            "km_driven": 0.15,
            "mileage": 0.45,
            "engine": 0.70,
            "max_power": 0.95,
            "torque_nm": 0.85,
            "seats": 0.25,
            "fuel": petrol_code,
            "seller_type": get_code("seller_type", "Dealer"),
            "transmission": manual_code,
            "owner": first_owner_code,
            "body_suv": 0,
            "body_sedan": 0,
            "body_coupe": 1,
            "is_premium_brand": 0,
        }

    if segment == 2:  # Budzet
        return {
            "year": 0.45,
            "selling_price": 0.20,
            "km_driven": 0.65,
            "mileage": 0.85,
            "engine": 0.35,
            "max_power": 0.35,
            "torque_nm": 0.35,
            "seats": 0.55,
            "fuel": petrol_code,
            "seller_type": get_code("seller_type", "Individual"),
            "transmission": manual_code,
            "owner": first_owner_code,
            "body_suv": 0,
            "body_sedan": 1,
            "body_coupe": 0,
            "is_premium_brand": 0,
        }

    if segment == 3:  # Porodica
        return {
            "year": 0.80,
            "selling_price": 0.55,
            "km_driven": 0.25,
            "mileage": 0.65,
            "engine": 0.55,
            "max_power": 0.55,
            "torque_nm": 0.55,
            "seats": 0.85,
            "fuel": int(np.random.choice([petrol_code, diesel_code])),
            "seller_type": get_code("seller_type", "Dealer"),
            "transmission": auto_code,
            "owner": first_owner_code,
            "body_suv": 1,
            "body_sedan": 0,
            "body_coupe": 0,
            "is_premium_brand": 0,
        }

    if segment == 4:  # Dizel
        return {
            "year": 0.70,
            "selling_price": 0.45,
            "km_driven": 0.45,
            "mileage": 0.75,
            "engine": 0.60,
            "max_power": 0.50,
            "torque_nm": 0.80,
            "seats": 0.55,
            "fuel": diesel_code,
            "seller_type": get_code("seller_type", "Dealer"),
            "transmission": manual_code,
            "owner": first_owner_code,
            "body_suv": 0,
            "body_sedan": 1,
            "body_coupe": 0,
            "is_premium_brand": 0,
        }

    raise ValueError("segment must be 1..4")
```

In [115…

```
print(f"\n{SEGMENT_NAMES[1]}")
display(recommend_for_user(make_user_pref(1), top_n=10))
```

```
Sport
```

| | name | year | selling_price | km_driven | fuel | transmission | owner |
|---|---|---|---|---|---|---|---|
| **1348** | Ford Mustang Shelby GT500 | 0.862069 | 0.078179 | 0.013999 | 4 | 1 | 1 |
| **825** | Chevrolet Corvette E-Ray | 1.000000 | 0.131792 | 0.002666 | 4 | 1 | 1 |
| **384** | Bentley Continental GT Speed | 0.896552 | 0.171801 | 0.015999 | 4 | 1 | 1 |
| **11** | Bentley Continental GT Mulliner | 0.931034 | 0.195807 | 0.013999 | 4 | 1 | 1 |
| **411** | Chevrolet Corvette ZR1 | 0.827586 | 0.115788 | 0.014666 | 4 | 1 | 1 |
| **1331** | Bentley Continental GT V8 | 0.827586 | 0.131792 | 0.027999 | 4 | 1 | 3 |
| **824** | Chevrolet Camaro LT1 Coupe | 0.896552 | 0.038169 | 0.019333 | 4 | 2 | 1 |
| **1350** | Chevrolet Corvette Stingray C7 | 0.724138 | 0.060575 | 0.031999 | 4 | 2 | 3 |
| **822** | Ford Mustang Shelby GT350R | 0.827586 | 0.073378 | 0.018666 | 4 | 2 | 3 |
| **1457** | Nissan GT-R Nismo Special | 0.862069 | 0.147795 | 0.013999 | 4 | 1 | 1 |

In [116…

```
print(f"\n{SEGMENT_NAMES[2]}")
display(recommend_for_user(make_user_pref(2), top_n=10))
```

```
Budzet
```

| | name | year | selling_price | km_driven | fuel | transmission | owner |
|---|---|---|---|---|---|---|---|
| **1057** | Hyundai Verna 1.4 CRDi | 0.689655 | 0.003961 | 0.165333 | 2 | 2 | 1 |
| **1513** | Hyundai Verna 1.6 SX | 0.586207 | 0.003361 | 0.133333 | 2 | 2 | 3 |
| **769** | Maruti Wagon R CNG LXI | 0.620690 | 0.001920 | 0.053333 | 1 | 2 | 3 |
| **23** | Honda City i DTEC VX | 0.655172 | 0.006322 | 0.133333 | 2 | 2 | 1 |
| **1437** | Hyundai Verna SX Diesel | 0.620690 | 0.004161 | 0.053333 | 2 | 2 | 1 |
| **734** | Maruti Swift VDI BSIV | 0.413793 | 0.001320 | 0.075253 | 2 | 2 | 1 |
| **1595** | Hyundai Verna 1.6 SX CRDi (O) | 0.551724 | 0.003361 | 0.085333 | 2 | 2 | 3 |
| **1052** | Maruti Wagon R Duo Lxi | 0.551724 | 0.002161 | 0.199999 | 3 | 2 | 1 |
| **192** | Mahindra XUV500 W6 2WD | 0.586207 | 0.003761 | 1.000000 | 2 | 2 | 1 |
| **497** | Maruti Ciaz VDi Plus | 0.655172 | 0.003441 | 0.096666 | 2 | 2 | 3 |

In [117…

```
print(f"\n{SEGMENT_NAMES[3]}")
display(recommend_for_user(make_user_pref(3), top_n=10))
```

```
Porodica
```

| | name | year | selling_price | km_driven | fuel | transmission | owner |
|---|---|---|---|---|---|---|---|
| **454** | Mahindra Scorpio VLX 2WD AIRBAG BSIV | 0.655172 | 0.004161 | 0.199999 | 2 | 2 | 4 |
| **305** | Ford Endeavour 3.2 Titanium AT 4X4 | 0.724138 | 0.018004 | 0.079999 | 2 | 1 | 3 |
| **1190** | Toyota Fortuner 4x2 Manual | 0.655172 | 0.010803 | 0.099999 | 2 | 2 | 1 |
| **1358** | Toyota Innova Crysta 2.4 VX MT 8S BSIV | 0.724138 | 0.013283 | 0.079999 | 2 | 2 | 1 |
| **825** | Chevrolet Corvette E-Ray | 1.000000 | 0.131792 | 0.002666 | 4 | 1 | 1 |
| **288** | Toyota Fortuner 4x4 MT | 0.689655 | 0.014868 | 0.079999 | 2 | 2 | 3 |
| **203** | Toyota Fortuner 2.8 4WD MT BSIV | 0.793103 | 0.025366 | 0.033333 | 2 | 2 | 1 |
| **216** | Toyota Fortuner 2.8 4WD AT BSIV | 0.793103 | 0.025366 | 0.039999 | 2 | 1 | 1 |
| **1259** | Mahindra XUV500 W8 4WD | 0.586207 | 0.003761 | 0.133333 | 2 | 2 | 2 |
| **1348** | Ford Mustang Shelby GT500 | 0.862069 | 0.078179 | 0.013999 | 4 | 1 | 1 |

In [118…

```
print(f"\n{SEGMENT_NAMES[4]}")
display(recommend_for_user(make_user_pref(4), top_n=10))
```

```
Dizel
```

| | name | year | selling_price | km_driven | fuel | transmission | owner |
|---|---|---|---|---|---|---|---|
| **1247** | BMW 5 Series 520d Sport Line | 0.482759 | 0.007562 | 0.053333 | 2 | 1 | 3 |
| **526** | BMW 3 Series 320d Luxury Line | 0.586207 | 0.010162 | 0.093333 | 2 | 1 | 3 |
| **522** | BMW 3 Series 320d Luxury Plus | 0.620690 | 0.010162 | 0.093333 | 2 | 1 | 3 |
| **1052** | Maruti Wagon R Duo Lxi | 0.551724 | 0.002161 | 0.199999 | 3 | 2 | 1 |
| **734** | Maruti Swift VDI BSIV | 0.413793 | 0.001320 | 0.075253 | 2 | 2 | 1 |
| **511** | Hyundai Verna 1.6 SX CRDi (O) | 0.586207 | 0.002961 | 0.091999 | 2 | 2 | 1 |
| **1261** | BMW 3 Series 320d Corporate Edition | 0.586207 | 0.006962 | 0.103333 | 2 | 1 | 3 |
| **1599** | Hyundai Verna 1.6 SX | 0.586207 | 0.003361 | 0.085333 | 2 | 2 | 3 |
| **1236** | Maruti Swift VDI | 0.620690 | 0.002761 | 0.043333 | 2 | 2 | 1 |
| **1091** | Maruti Wagon R LXI CNG | 0.551724 | 0.001360 | 0.091333 | 1 | 2 | 1 |

```
In [ ]:
```