Sistem preporuka polovnih automobila zasnovan na Two-Tower arhitekturi

Cilj ovog projekta je izgradnja sistema za preporuku polovnih automobila koji uci zajednicki embedding prostor za korisnike i vozila koristeci Two-Tower neuronsku arhitekturu. Model povezuje sinteticke korisnicke preferencije i karakteristike automobila kako bi identifikovao najrelevantnije preporuke na osnovu njihove slicnosti.

In [132…

```
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("./data/car-details-v4.csv", low_memory=False)
df.head()
```

Out[132…

	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

Missing data

In [133…

```
df.isna().sum()
```

Out[133…

```
name              0
year              0
selling_price     0
km_driven         0
fuel              0
seller_type       0
transmission      0
owner             0
mileage          45
engine           45
max_power        43
torque           45
seats            45
dtype: int64
```

In [134…

```
missing_cnt = df.isna().sum().sort_values(ascending=False)
missing_pct = (df.isna().mean() * 100).round(2).sort_values(ascending=Fal

display(pd.DataFrame({"missing_count": missing_cnt, "missing_pct": missin
```

	missing_count	missing_pct
mileage	45	2.75
engine	45	2.75
torque	45	2.75
seats	45	2.75
max_power	43	2.63

Prepare data

In [135…

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

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 = df.drop(columns=["torque"])
df["seats"] = pd.to_numeric(df["seats"], errors="coerce")
```

Feature engineering

In [136…

```
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
```

Clean categorical columns

In [137…

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

Out[137…
```
name               0
year               0
selling_price      0
km_driven          0
fuel               0
seller_type        0
transmission       0
owner              0
mileage            0
engine             0
max_power          0
seats              0
torque_nm          0
body_coupe         0
body_sedan         0
body_suv           0
brand              0
is_premium_brand   0
dtype: int64
```

In [138…
```
df.head()
```

Out[138…

	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

Outlier handling

In [139…
```
clip_cols = ["selling_price", "km_driven", "engine", "max_power", "torque

for c in clip_cols:
    low, high = df[c].quantile([0.01, 0.99])
    df[c] = df[c].clip(lower=low, upper=high)
```

```
df.describe()
```

Out[139…

	year	selling_price	km_driven	mileage	engine	m
count	1636.000000	1.636000e+03	1636.000000	1636.000000	1636.000000	163
mean	2014.342298	1.714498e+06	64065.471363	18.091589	1667.842910	1
std	4.453794	3.925769e+06	44116.193273	5.196142	922.386098	1
min	1995.000000	5.500000e+04	4000.000000	0.000000	624.000000	
25%	2012.000000	2.600000e+05	29000.000000	15.370000	1197.000000	
50%	2015.000000	4.970000e+05	58788.500000	18.600000	1396.000000	
75%	2018.000000	8.204992e+05	90000.000000	21.660000	1991.000000	1
max	2024.000000	2.450000e+07	217950.950000	32.520000	5998.000000	68

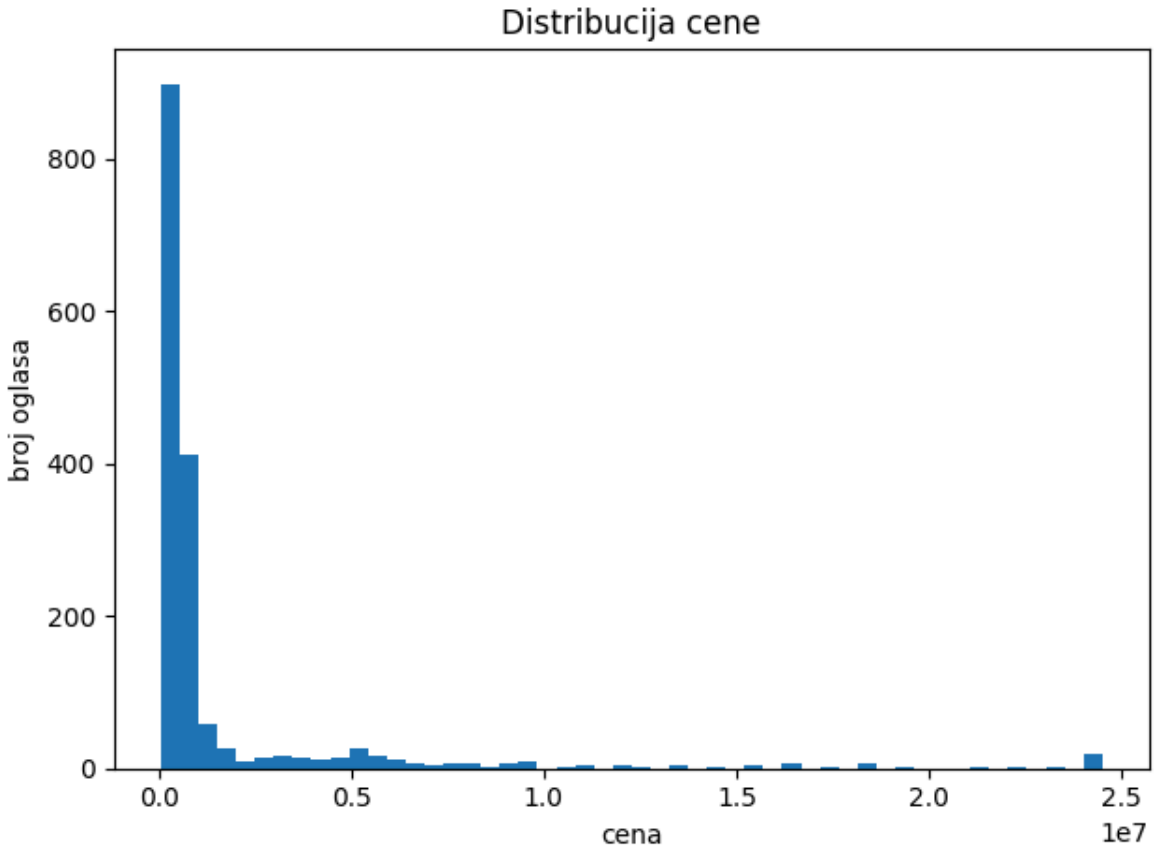
Nakon percentilnog ograničavanja (1–99%), uklonjen je uticaj ekstremnih vrednosti, cime je obezbeđen stabilniji trening i manji rizik od overfitting-a.

EDA (Exploratory Data Analysis)

In [140…

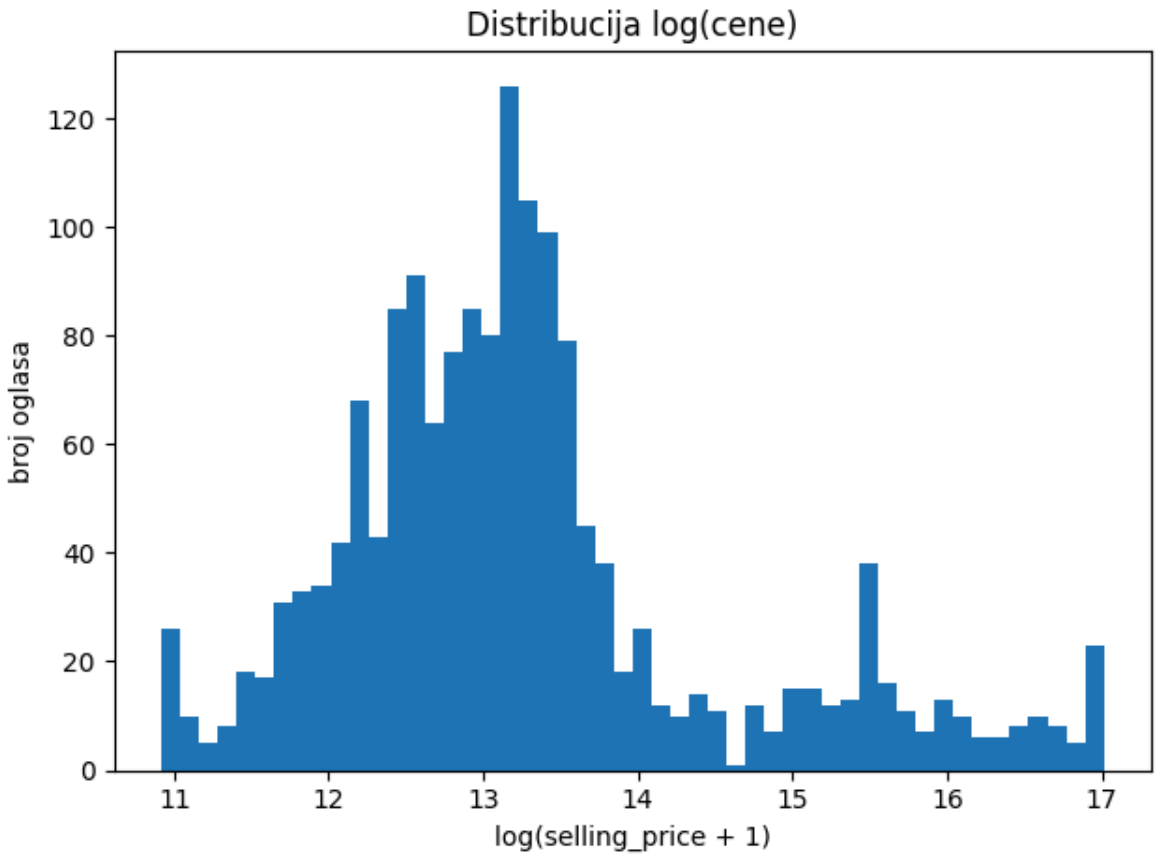
```
import matplotlib.pyplot as plt

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()
```



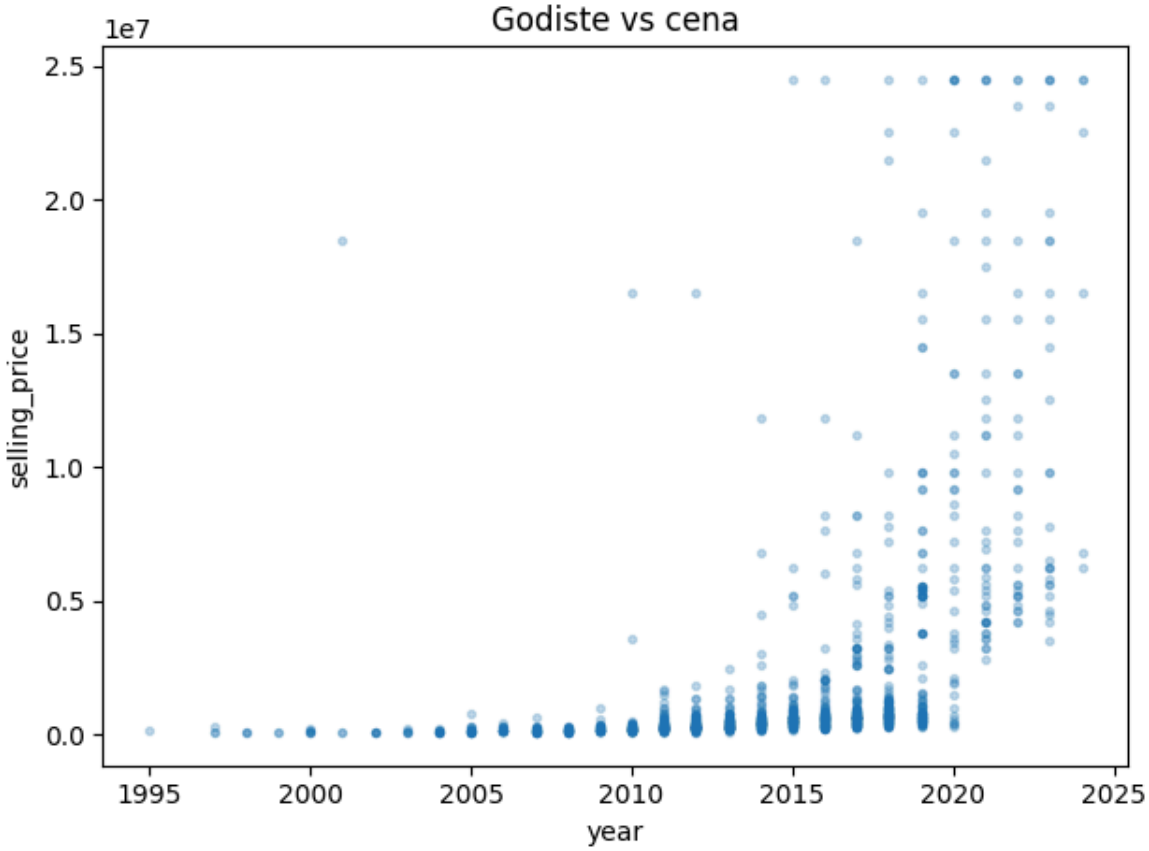
In [141…

```
plt.figure()
plt.hist(np.log1p(df["selling_price"]), bins=50)
plt.title("Distribucija log(cene)")
plt.xlabel("log(selling_price + 1)")
plt.ylabel("broj oglasa")
plt.tight_layout()
plt.show()
```



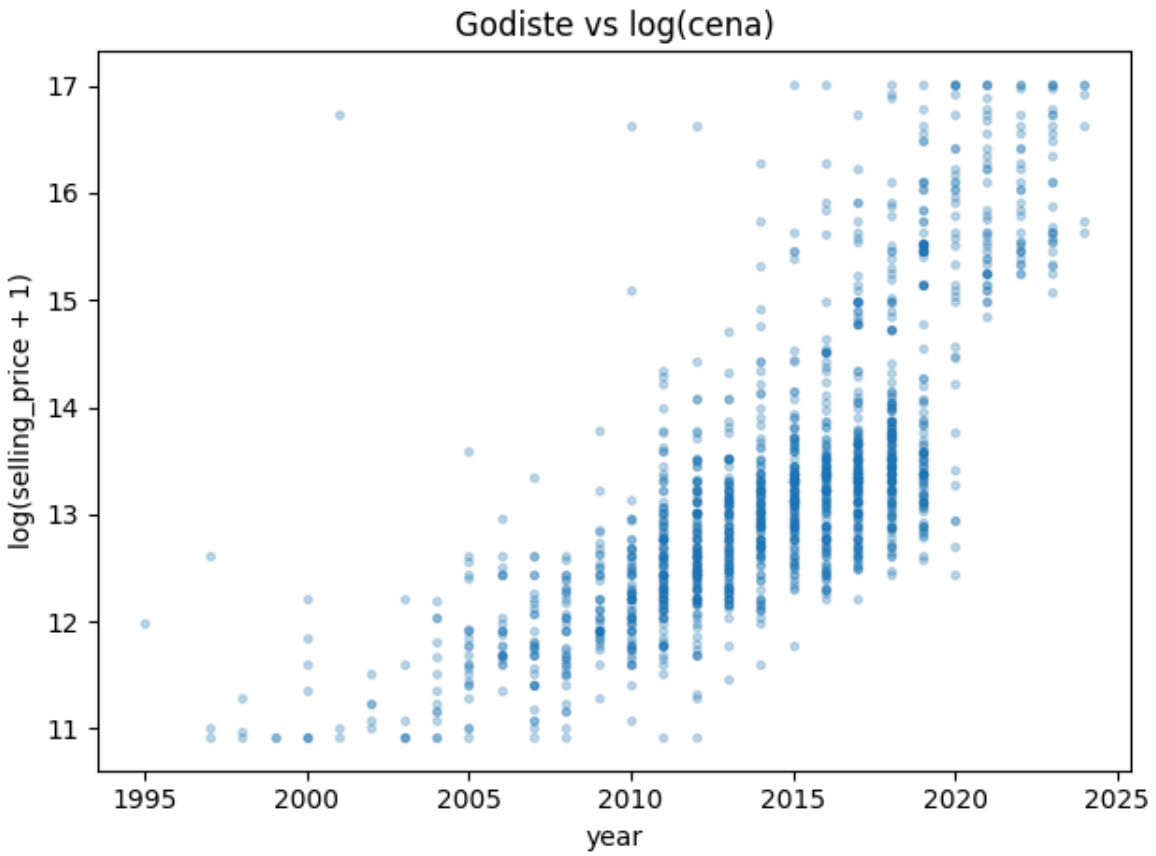
In [142…

```
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()
```



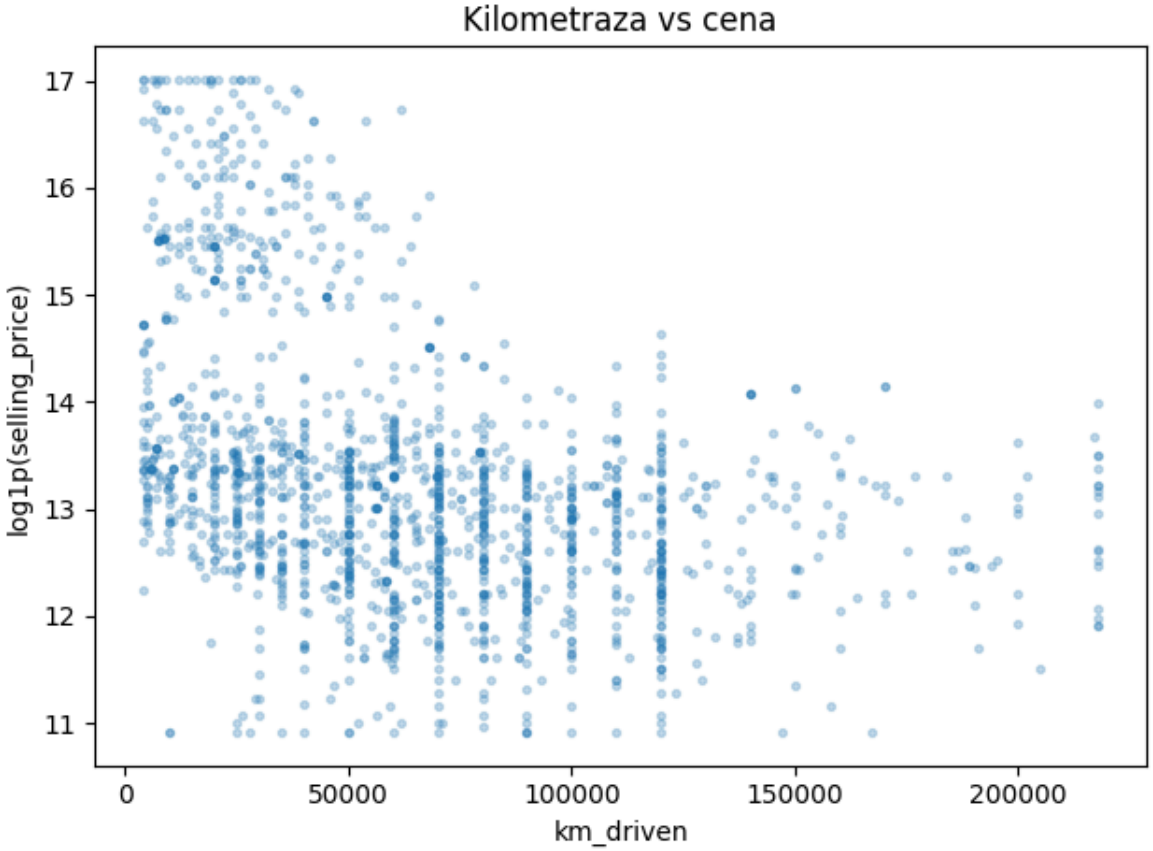
In [143…

```
plt.figure()
plt.scatter(df["year"], np.log1p(df["selling_price"]), s=8, alpha=0.25)
plt.title("Godiste vs log(cena)")
plt.xlabel("year")
plt.ylabel("log(selling_price + 1)")
plt.tight_layout()
plt.show()
```



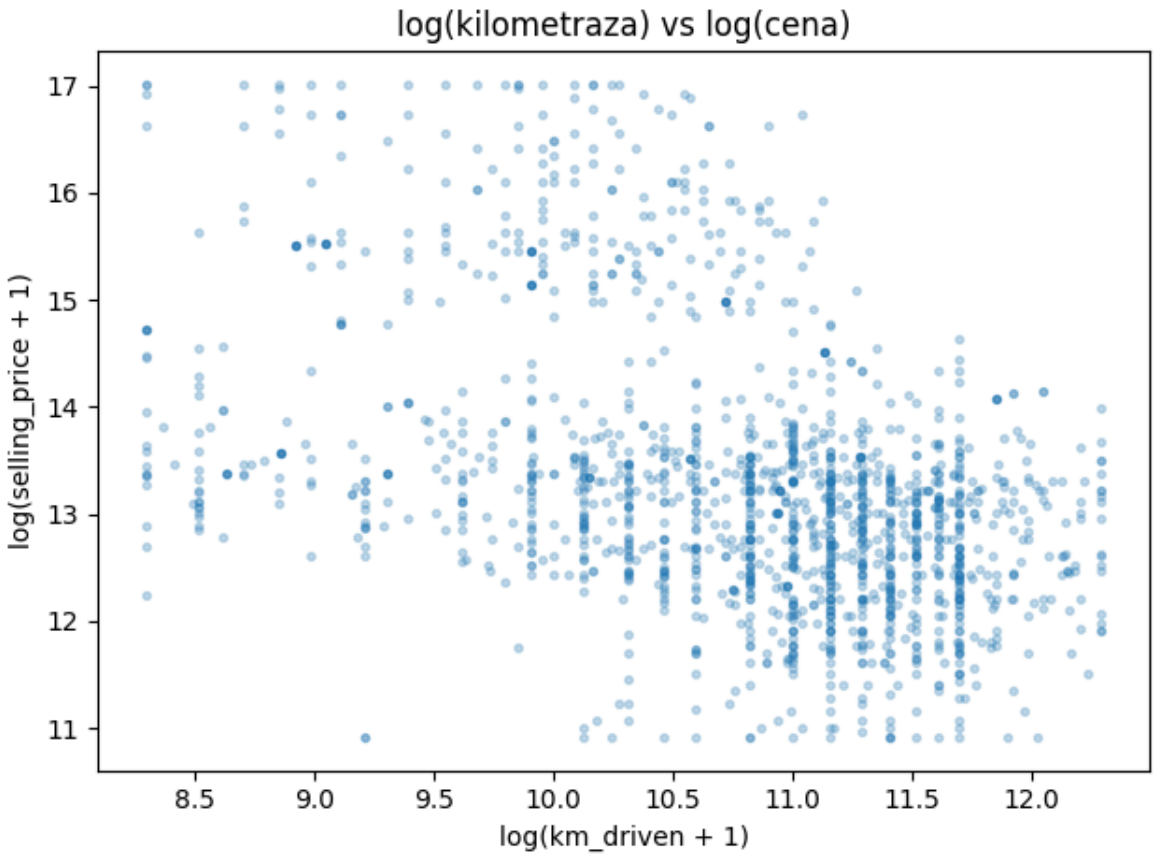
In [144…

```
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()
```



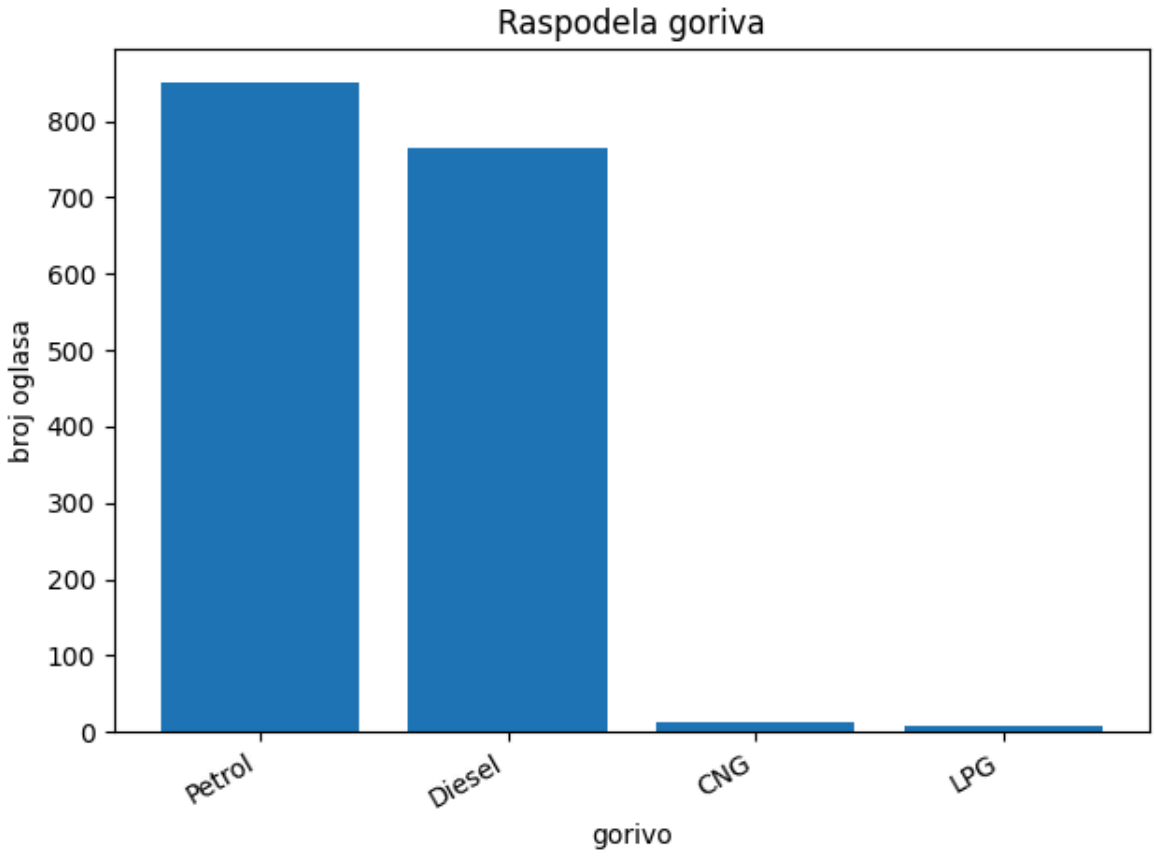
In [145…

```
plt.figure()
plt.scatter(np.log1p(df["km_driven"]), np.log1p(df["selling_price"]), s=8
plt.title("log(kilometraza) vs log(cena)")
plt.xlabel("log(km_driven + 1)")
plt.ylabel("log(selling_price + 1)")
plt.tight_layout()
plt.show()
```



In [146…

```
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()
```



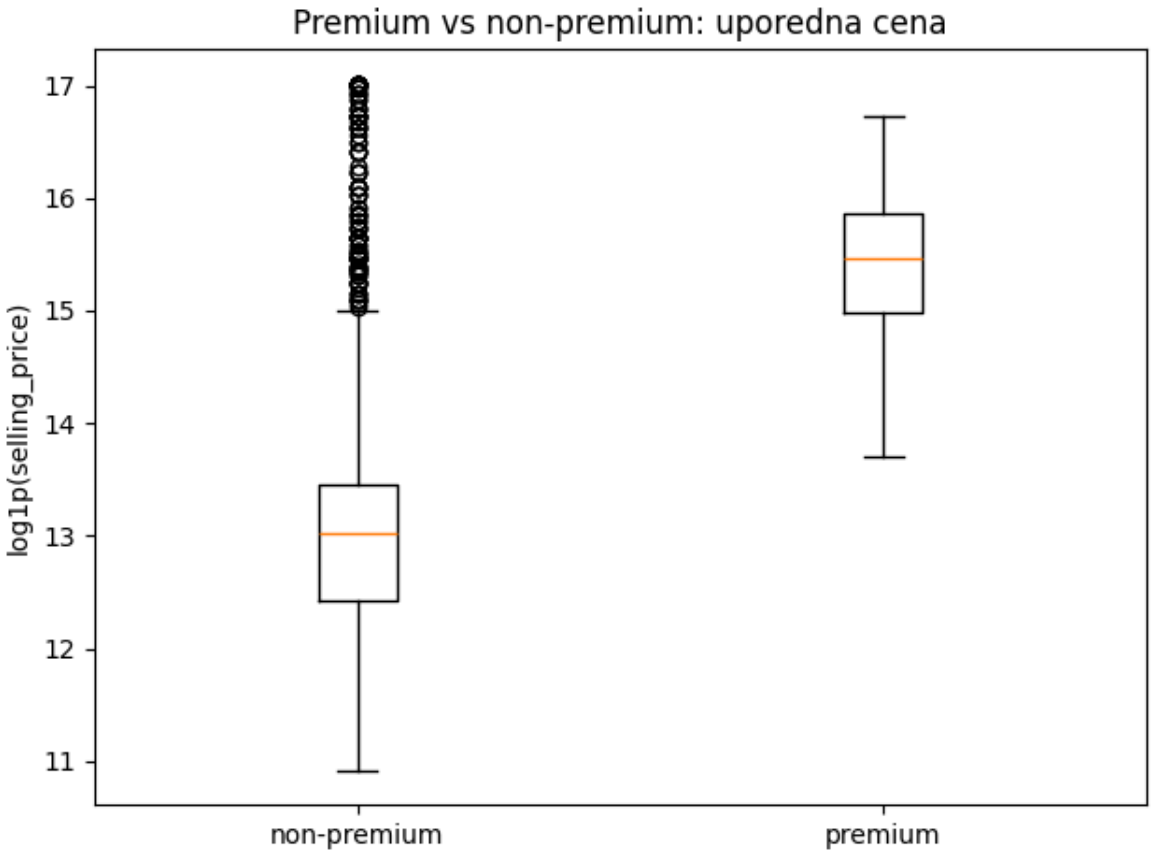
1. Metan (CNG)
2. Dizel
3. Plin (LPG)
4. Benzin

Vidimo da vecina oglasa koristi benzin ili dizel, dok su alternativna goriva (CNG, LPG) slabo zastupljena, sto moze uticati na ucenje embeddinga za ovu kategoriju.

In [147…

```
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()],
    tick_labels=["non-premium", "premium"]
)
plt.title("Premium vs non-premium: uporedna cena")
plt.ylabel("log1p(selling_price)")
plt.tight_layout()
plt.show()
```



Preprocesiranje/Enkodiranje

In [148…

```
from sklearn.preprocessing import MinMaxScaler

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

CAR_CAT_COLS = ["fuel", "seller_type", "transmission", "owner"]
CAR_BIN_COLS = ["body_suv", "body_sedan", "body_coupe", "is_premium_brand

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

car_scaler = MinMaxScaler()
df[CAR_NUM_COLS] = car_scaler.fit_transform(df[CAR_NUM_COLS])

car_cat_maps = {}
car_cat_sizes = {}
```

```
for c in CAR_CAT_COLS:
    cats = sorted(df[c].unique())
    if "Unknown" not in cats:
        cats = ["Unknown"] + cats

    car_cat_maps[c] = {k: i for i, k in enumerate(cats)}
    car_cat_sizes[c] = len(cats)

    df[c] = df[c].map(car_cat_maps[c]).fillna(car_cat_maps[c]["Unknown"])

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

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

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

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

first_owner_code = get_car_code("owner", "First Owner")
second_owner_code = get_car_code("owner", "Second Owner")

df_items = df[CAR_NUM_COLS + CAR_CAT_COLS + CAR_BIN_COLS].copy()
df_items.head()
```

Out[148…

	year	km_driven	mileage	engine	max_power	torque_nm	seats	fuel
0	0.620690	0.532832	0.738007	0.092296	0.050548	0.120095	0.375	2
1	0.620690	0.303808	0.686347	0.178266	0.136816	0.238763	0.375	2
2	0.689655	0.098153	0.641144	0.106624	0.070675	0.066587	0.375	4
3	0.689655	0.448701	0.519680	0.106624	0.068714	0.065101	0.375	4
4	0.689655	0.495441	0.817651	0.116115	0.056675	0.155767	0.375	2

In [149…

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

Out[149…

```
year                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
```

Users data

In [150…

```
USER_CSV_PATH = "./data/user-details.csv"
users_df = pd.read_csv(USER_CSV_PATH)

REQUIRED_USER_COLS = [
    "age",
    "has_family",
    "annual_km",
    "primary_use",
    "drive_style",
    "budget_level",
    "comfort_priority",
    "performance_priority",
    "eco_priority",
    "space_need",
    "reliability_priority",
    "offroad_need",
    "transmission_pref",
    "fuel_pref",
]

missing = [c for c in REQUIRED_USER_COLS if c not in users_df.columns]
if missing:
    raise ValueError(f"Missing columns in user CSV: {missing}")

users_df.head()
```

Out[150…

	age	has_family	annual_km	primary_use	drive_style	budget_level	comfort_p
0	56	1	16284	daily	calm	0.82	
1	59	0	7747	daily	normal	0.12	
2	21	1	13433	daily	calm	0.35	
3	59	1	14692	weekend	normal	0.42	
4	62	0	7568	mixed	calm	0.71	

In [151…

```
for c in [
    "age",
    "has_family",
    "annual_km",
    "budget_level",
    "comfort_priority",
    "performance_priority",
    "eco_priority",
    "space_need",
    "reliability_priority",
    "offroad_need",
]:
    users_df[c] = pd.to_numeric(users_df[c], errors="coerce")

for c in ["primary_use", "drive_style", "transmission_pref", "fuel_pref"]:
    users_df[c] = users_df[c].astype(str).str.strip()
```

In [152…

```
users_df = users_df.dropna(subset=["age", "has_family", "annual_km"]).cop

users_df["age"] = users_df["age"].clip(18, 80).astype(int)
users_df["has_family"] = users_df["has_family"].clip(0, 1).astype(int)
users_df["annual_km"] = users_df["annual_km"].clip(1000, 100000).astype(i

for c in [
    "budget_level",
    "comfort_priority",
    "performance_priority",
    "eco_priority",
    "space_need",
    "reliability_priority",
    "offroad_need",
]:
    users_df[c] = users_df[c].clip(0.0, 1.0)

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

Out[152…

	age	has_family	annual_km	primary_use	drive_style	budget_level	comfort_p
0	56	1	16284	daily	calm	0.82	
1	59	0	7747	daily	normal	0.12	
2	21	1	13433	daily	calm	0.35	
3	59	1	14692	weekend	normal	0.42	
4	62	0	7568	mixed	calm	0.71	

In [153…

```
USER_NUM_COLS = [
    "age",
    "annual_km",
    "budget_level",
    "comfort_priority",
    "performance_priority",
    "eco_priority",
    "space_need",
    "reliability_priority",
    "offroad_need",
]

USER_BIN_COLS = ["has_family"]
USER_CAT_COLS = ["primary_use", "drive_style", "transmission_pref", "fuel

users_df[USER_NUM_COLS + USER_BIN_COLS].isna().sum()
```

Out[153…
```
age                    0
annual_km              0
budget_level           0
comfort_priority       0
performance_priority   0
eco_priority           0
space_need             0
reliability_priority   0
offroad_need           0
has_family             0
dtype: int64
```

Bodovanje automobila po segmentima

In [154…
```python
def _pick_fuel_code_from_pref(fuel_pref: str, annual_km: int) -> int:
    if fuel_pref == "Petrol":
        return petrol_code
    if fuel_pref == "Diesel":
        return diesel_code
    return diesel_code if annual_km >= 18000 else petrol_code


def _pick_trans_code_from_pref(trans_pref: str, primary_use: str, comfort
    if trans_pref == "Manual":
        return manual_code
    if trans_pref == "Automatic":
        return auto_code
    if primary_use == "daily" and comfort >= 0.55:
        return auto_code
    return manual_code


def profile_to_car_pref(user_row: pd.Series) -> dict:
    """
    Mapira driver-like user u internu car-preferencu (car feature space).
    Sve numeric vrednosti su u [0,1] da odgovaraju df_items skaliranom sa
    """
    has_family = int(user_row["has_family"])
    annual_km = int(user_row["annual_km"])

    primary_use = str(user_row["primary_use"]).strip()
    drive_style = str(user_row["drive_style"]).strip()

    budget = float(user_row["budget_level"])
    comfort = float(user_row["comfort_priority"])
    perf = float(user_row["performance_priority"])
    eco = float(user_row["eco_priority"])
    space = float(user_row["space_need"])
    rel = float(user_row["reliability_priority"])
    offroad = float(user_row["offroad_need"])

    year = np.clip(0.35 + 0.45 * rel + 0.15 * budget + 0.10 * (primary_us

    # smanjena tezina budzeta da ne gura Bentley/Rolls svuda
    selling_price = np.clip(0.20 + 0.60 * budget + 0.10 * comfort, 0.0, 1

    km_driven = np.clip(0.55 - 0.25 * rel + 0.20 * (primary_use == "weeke

    mileage = np.clip(0.35 + 0.60 * eco, 0.0, 1.0)
```

```
    engine = np.clip(0.20 + 0.70 * perf, 0.0, 1.0)
    max_power = np.clip(0.15 + 0.80 * perf, 0.0, 1.0)
    torque_nm = np.clip(0.20 + 0.75 * perf, 0.0, 1.0)

    seats = np.clip(0.25 + 0.75 * (0.65 * space + 0.35 * has_family), 0.0

    body_suv = 1.0 if (offroad >= 0.45 or (space >= 0.65 and has_family =
    body_coupe = 1.0 if (perf >= 0.70 and has_family == 0 and space <= 0.
    body_sedan = 1.0 if (body_suv == 0.0 and body_coupe == 0.0) else 0.0

    # manje agresivan premium signal
    is_premium_brand = 1.0 if (budget >= 0.80 and comfort >= 0.75) else 0

    fuel_code = _pick_fuel_code_from_pref(str(user_row["fuel_pref"]).stri
    trans_code = _pick_trans_code_from_pref(str(user_row["transmission_pr

    seller_code = get_car_code("seller_type", "Dealer") if rel >= 0.55 el
    owner_code = first_owner_code if rel >= 0.55 else second_owner_code

    return {
        "year": float(year),
        "selling_price": float(selling_price),
        "km_driven": float(km_driven),
        "mileage": float(mileage),
        "engine": float(engine),
        "max_power": float(max_power),
        "torque_nm": float(torque_nm),
        "seats": float(seats),
        "fuel": int(fuel_code),
        "seller_type": int(seller_code),
        "transmission": int(trans_code),
        "owner": int(owner_code),
        "body_suv": float(body_suv),
        "body_sedan": float(body_sedan),
        "body_coupe": float(body_coupe),
        "is_premium_brand": float(is_premium_brand),
    }


def score_items_for_user_profile(user_row: pd.Series, cars_df: pd.DataFra
    """
    Score svih automobila za jedan driver-like user.
    Vraca score vector (float32).
    """
    pref = profile_to_car_pref(user_row)

    user_num = np.array([pref[c] for c in CAR_NUM_COLS], dtype="float32")
    car_num = cars_df[CAR_NUM_COLS].values.astype("float32")

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

    score += 0.8 * (cars_df["fuel"].values == pref["fuel"]).astype("float
    score += 0.6 * (cars_df["transmission"].values == pref["transmission"
    score += 0.2 * (cars_df["seller_type"].values == pref["seller_type"])
    score += 0.2 * (cars_df["owner"].values == pref["owner"]).astype("flo

    score += 2.0 * (cars_df["body_suv"].values.astype("float32") * pref["
    score += 2.0 * (cars_df["body_coupe"].values.astype("float32") * pref
```

```
    score += 0.8 * (cars_df["body_sedan"].values.astype("float32") * pref

    score += 0.2 * (cars_df["is_premium_brand"].values.astype("float32")

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

Generisanje trening parova (pozitivni/negativni)

In [173…

```
def generate_training_pairs(users_df, cars_df, n_pos=15, n_neg=15, hard_n
    # ITEM (cars) tensors
    cars_num = cars_df[CAR_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[CAR_BIN_COLS].values.astype("float32")

    # USER tensors
    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_user_profile(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 + 200)
            else idx_sorted[:-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])

        pref = profile_to_car_pref(user)

        u_num = np.array([pref[c] for c in CAR_NUM_COLS], dtype="float32"
        u_fuel = int(pref["fuel"])
```

```
        u_seller = int(pref["seller_type"])
        u_trans = int(pref["transmission"])
        u_owner = int(pref["owner"])
        u_bin = np.array([pref[c] for c in CAR_BIN_COLS], dtype="float32"

        def add(indices, label: float):
            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 [174…

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

embedding_dim = 32
num_numeric = len(CAR_NUM_COLS)
num_bin = len(CAR_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 (car features)
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 [175…

```
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),
    metrics=[
        tf.keras.metrics.AUC(from_logits=True, name="auc"),
        tf.keras.metrics.BinaryAccuracy(threshold=0.0, name="acc"),
    ],
)

model.summary()
```

Model: "two_tower"

Layer (type)	Output Shape	Param #	Connected t
user_fuel (InputLayer)	(None)	0	-
user_seller (InputLayer)	(None)	0	-
user_trans (InputLayer)	(None)	0	-
user_owner (InputLayer)	(None)	0	-
item_fuel (InputLayer)	(None)	0	-
item_seller (InputLayer)	(None)	0	-
item_trans (InputLayer)	(None)	0	-
item_owner (InputLayer)	(None)	0	-
embedding_64 (Embedding)	(None, 4)	20	user_fuel[0
embedding_65 (Embedding)	(None, 4)	16	user_seller
embedding_66 (Embedding)	(None, 4)	12	user_trans
embedding_67 (Embedding)	(None, 4)	20	user_owner
embedding_68 (Embedding)	(None, 4)	20	item_fuel[0
embedding_69 (Embedding)	(None, 4)	16	item_seller
embedding_70 (Embedding)	(None, 4)	12	item_trans
embedding_71 (Embedding)	(None, 4)	20	item_owner
user_num (InputLayer)	(None, 7)	0	-
user_bin (InputLayer)	(None, 4)	0	-
reshape_64 (Reshape)	(None, 4)	0	embedding_6
reshape_65 (Reshape)	(None, 4)	0	embedding_6
reshape_66	(None, 4)	0	embedding_6

(Reshape)			
reshape_67 (Reshape)	(None, 4)	0	embedding_6
item_num (InputLayer)	(None, 7)	0	–
item_bin (InputLayer)	(None, 4)	0	–
reshape_68 (Reshape)	(None, 4)	0	embedding_6
reshape_69 (Reshape)	(None, 4)	0	embedding_6
reshape_70 (Reshape)	(None, 4)	0	embedding_7
reshape_71 (Reshape)	(None, 4)	0	embedding_7
concatenate_16 (Concatenate)	(None, 27)	0	user_num[0] user_bin[0] reshape_64 reshape_65 reshape_66 reshape_67
concatenate_17 (Concatenate)	(None, 27)	0	item_num[0] item_bin[0] reshape_68 reshape_69 reshape_70 reshape_71
dense_48 (Dense)	(None, 128)	3,584	concatenate
dense_51 (Dense)	(None, 128)	3,584	concatenate
dropout_16 (Dropout)	(None, 128)	0	dense_48[0]
dropout_17 (Dropout)	(None, 128)	0	dense_51[0]
dense_49 (Dense)	(None, 64)	8,256	dropout_16
dense_52 (Dense)	(None, 64)	8,256	dropout_17
dense_50 (Dense)	(None, 32)	2,080	dense_49[0]
dense_53 (Dense)	(None, 32)	2,080	dense_52[0]
user_l2 (Lambda)	(None, 32)	0	dense_50[0]
item_l2 (Lambda)	(None, 32)	0	dense_53[0]
dot (Dot)	(None, 1)	0	user_l2[0] item_l2[0]

Total params: 27,976 (109.28 KB)

Trainable params: 27,976 (109.28 KB)

Non-trainable params: 0 (0.00 B)

In [176…

```
(
    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,
    validation_split=0.2,
    shuffle=True,
)


def build_item_inputs_from_df(cars_df: pd.DataFrame):
    num = cars_df[CAR_NUM_COLS].values.astype("float32")
    bin_ = cars_df[CAR_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,
)
```

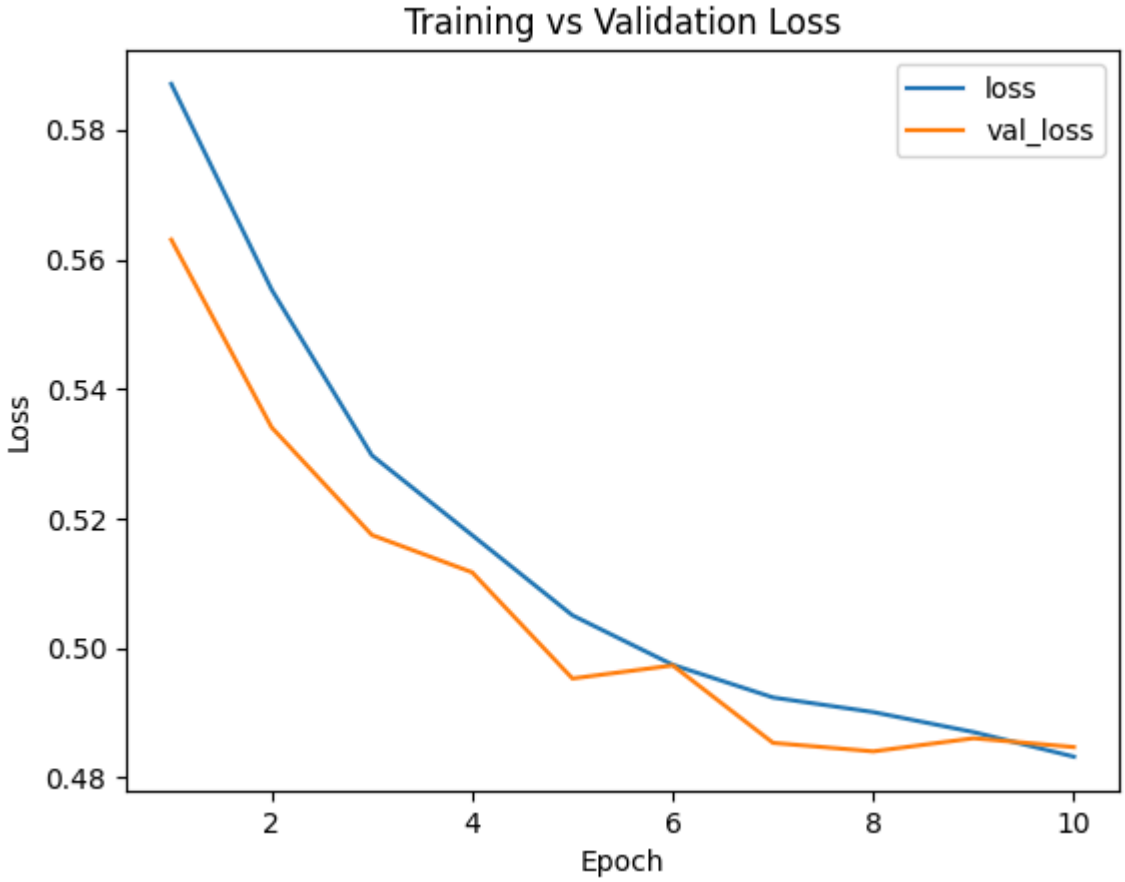
```
Epoch 1/10
113/113 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - acc: 0.7092 - auc: 0.7797 - los
s: 0.5871 - val_acc: 0.7289 - val_auc: 0.8339 - val_loss: 0.5630
Epoch 2/10
113/113 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - acc: 0.7418 - auc: 0.8269 - los
s: 0.5553 - val_acc: 0.7694 - val_auc: 0.8555 - val_loss: 0.5341
Epoch 3/10
113/113 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - acc: 0.7733 - auc: 0.8606 - los
s: 0.5297 - val_acc: 0.7894 - val_auc: 0.8715 - val_loss: 0.5174
Epoch 4/10
113/113 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - acc: 0.7964 - auc: 0.8756 - los
s: 0.5174 - val_acc: 0.8122 - val_auc: 0.8778 - val_loss: 0.5117
Epoch 5/10
113/113 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - acc: 0.8099 - auc: 0.8876 - los
s: 0.5051 - val_acc: 0.8061 - val_auc: 0.8987 - val_loss: 0.4953
Epoch 6/10
113/113 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - acc: 0.8186 - auc: 0.8951 - los
s: 0.4974 - val_acc: 0.8011 - val_auc: 0.8957 - val_loss: 0.4973
Epoch 7/10
113/113 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - acc: 0.8228 - auc: 0.9008 - los
s: 0.4924 - val_acc: 0.8322 - val_auc: 0.9104 - val_loss: 0.4854
Epoch 8/10
113/113 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - acc: 0.8264 - auc: 0.9035 - los
s: 0.4901 - val_acc: 0.8261 - val_auc: 0.9089 - val_loss: 0.4841
Epoch 9/10
113/113 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - acc: 0.8292 - auc: 0.9085 - los
s: 0.4870 - val_acc: 0.8233 - val_auc: 0.9192 - val_loss: 0.4861
Epoch 10/10
113/113 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - acc: 0.8336 - auc: 0.9099 - los
s: 0.4832 - val_acc: 0.8333 - val_auc: 0.9197 - val_loss: 0.4847
```

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

In [177…

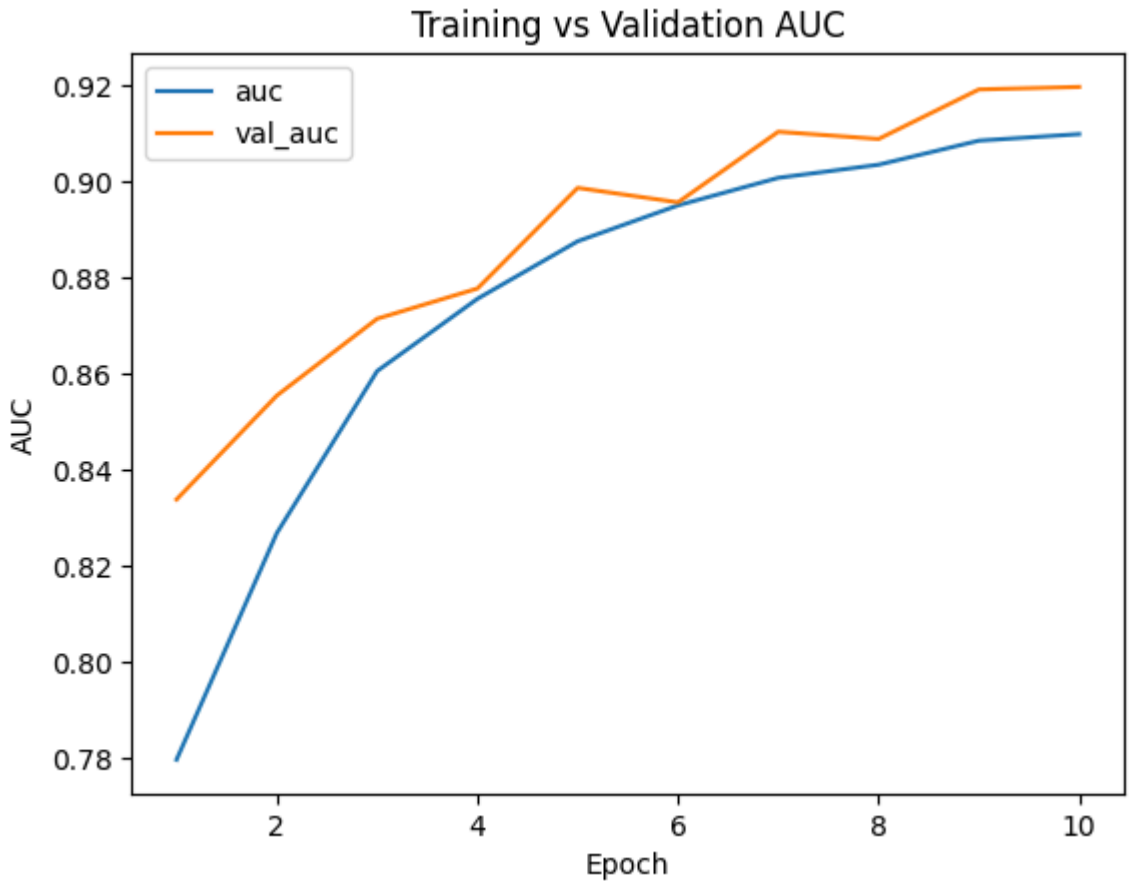
```python
epochs = range(1, len(history.history["loss"]) + 1)

plt.figure()
plt.plot(epochs, history.history["loss"], label="loss")
if "val_loss" in history.history:
    plt.plot(epochs, history.history["val_loss"], label="val_loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Training vs Validation Loss")
plt.legend()
plt.show()
```



In [178…

```
if "auc" in history.history:
    plt.figure()
    plt.plot(epochs, history.history["auc"], label="auc")
    if "val_auc" in history.history:
        plt.plot(epochs, history.history["val_auc"], label="val_auc")
    plt.xlabel("Epoch")
    plt.ylabel("AUC")
    plt.title("Training vs Validation AUC")
    plt.legend()
    plt.show()
```



Skorovi za trening parove

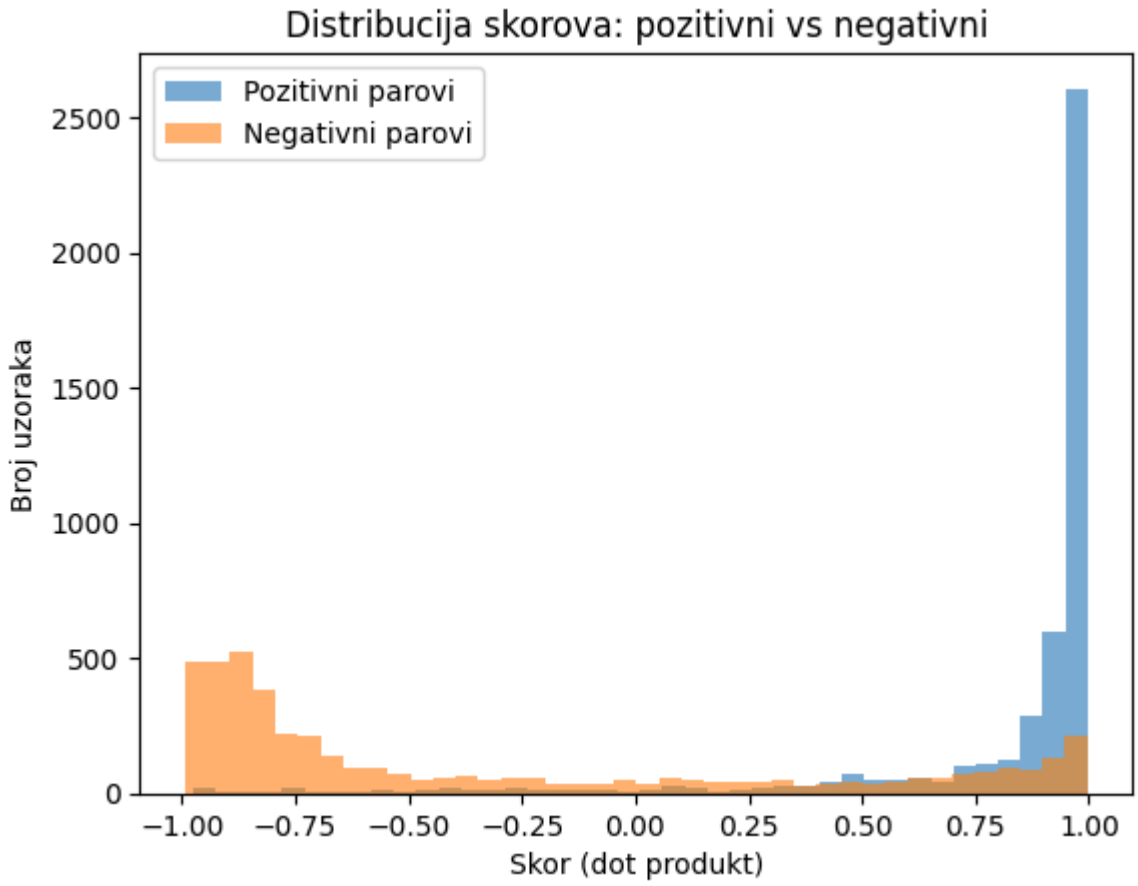
In [179…

```
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)

pos_scores = train_scores[y == 1]
neg_scores = train_scores[y == 0]

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()
```



In [180…
```
print("pos median:", np.median(pos_scores), "neg median:", np.median(neg_
print("pos<=0:", (pos_scores <= 0).mean(), "neg>=0:", (neg_scores >= 0).m
```

```
pos median: 0.96276736 neg median: -0.7112465
pos<=0: 0.04755555555555555 neg>=0: 0.28955555555555557
```

In [181…
```
def recommend_for_user_profile(user_profile: dict, top_n=10):
    """
    user_profile: driver-like dict (age, has_family, annual_km, primary_u
    Interno se mapira na car-preferencu, pa se radi retrieval nad item_em
    """
    pref = profile_to_car_pref(pd.Series(user_profile))

    user_num = np.array([[pref[c] for c in CAR_NUM_COLS]], dtype="float32
    user_bin = np.array([[pref[c] for c in CAR_BIN_COLS]], dtype="float32

    user_fuel = np.array([pref["fuel"]], dtype="int32")
    user_seller = np.array([pref["seller_type"]], dtype="int32")
    user_trans = np.array([pref["transmission"]], dtype="int32")
    user_owner = np.array([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()
    out["score"] = selected_scores
    return out
```

Test

In [182…

```
user_sporty_young = {
    "age": 26,
    "has_family": 0,
    "annual_km": 9000,
    "primary_use": "weekend",
    "drive_style": "sporty",
    "budget_level": 0.70,
    "comfort_priority": 0.45,
    "performance_priority": 0.90,
    "eco_priority": 0.30,
    "space_need": 0.25,
    "reliability_priority": 0.50,
    "offroad_need": 0.05,
    "transmission_pref": "Manual",
    "fuel_pref": "Petrol",
}
recommend_for_user_profile(user_sporty_young, top_n=10)
```

Out [182…

	name	year	selling_price	km_driven	fuel	transmission	owner
825	Chevrolet Corvette E-Ray	1.000000	16500000	0.000000	4	1	1
411	Chevrolet Corvette ZR1	0.827586	14500000	0.084131	4	1	1
1350	Chevrolet Corvette Stingray C7	0.724138	7600000	0.205655	4	2	3
1348	Ford Mustang Shelby GT500	0.862069	9800000	0.079457	4	1	1
11	Bentley Continental GT Mulliner	0.931034	24500000	0.079457	4	1	1
824	Chevrolet Camaro LT1 Coupe	0.896552	4800000	0.116849	4	2	1
384	Bentley Continental GT Speed	0.896552	21500000	0.093479	4	1	1
1347	Ford Mustang GT Performance	0.862069	5800000	0.102827	4	2	1
1579	Maserati Quattroporte Trofeo	0.931034	13500000	0.070110	4	1	1
822	Ford Mustang Shelby GT350R	0.827586	9200000	0.112175	4	2	3

In [183…

```
user_family = {
    "age": 38,
    "has_family": 1,
    "annual_km": 18000,
    "primary_use": "daily",
    "drive_style": "calm",
    "budget_level": 0.50,
    "comfort_priority": 0.75,
    "performance_priority": 0.40,
    "eco_priority": 0.55,
    "space_need": 0.80,
    "reliability_priority": 0.80,
    "offroad_need": 0.30,
    "transmission_pref": "Automatic",
    "fuel_pref": "Diesel",
}
recommend_for_user_profile(user_family, top_n=10)
```

Out [183…

	name	year	selling_price	km_driven	fuel	transmission	owner	
362	Toyota Innova Crysta 2.8 GX AT 8S BSIV	0.793103	1800000	0.074783	2	1	1	0
1233	Toyota Fortuner 4x4 AT	0.724138	1750000	0.224350	2	1	1	0
36	Maruti Swift Dzire AMT ZDI	0.724138	650000	0.215003	2	1	3	0
1158	Mahindra Scorpio VLX AT AIRBAG BSIV	0.517241	509999	0.434679	2	1	3	0
1254	Mahindra Scorpio VLS AT 2.2 mHAWK	0.551724	450000	0.425331	2	1	3	0
209	Ford Endeavour 3.0L 4X4 AT	0.551724	975000	0.418171	2	1	3	0
1397	Ford Endeavour 2.2 Titanium AT 4X2	0.724138	2100000	0.378591	2	1	3	0.
305	Ford Endeavour 3.2 Titanium AT 4X4	0.724138	2280000	0.542180	2	1	3	0.
451	Skoda Octavia Style Plus 2.0 TDI AT	0.827586	2600000	0.032718	2	1	1	0
446	MG Hector Sharp DCT Dualtone	0.862069	1900000	0.000000	4	1	1	0

In [184…

```
user_budget_city = {
    "age": 29,
    "has_family": 0,
    "annual_km": 11000,
    "primary_use": "daily",
    "drive_style": "normal",
```

```
    "budget_level": 0.25,
    "comfort_priority": 0.50,
    "performance_priority": 0.35,
    "eco_priority": 0.70,
    "space_need": 0.40,
    "reliability_priority": 0.60,
    "offroad_need": 0.10,
    "transmission_pref": "Manual",
    "fuel_pref": "Any",
}
recommend_for_user_profile(user_budget_city, top_n=10)
```

Out [184…

	name	year	selling_price	km_driven	fuel	transmission	owner	
1542	Honda City i VTEC VX Option	0.724138	750000	0.056793	4	2	1	0
1544	Honda City i VTEC V	0.689655	600000	0.112928	4	2	1	0.
1199	Honda City i VTEC VX	0.793103	925000	0.116382	4	2	1	0
1533	Honda City i-VTEC V	0.551724	325000	0.168263	4	2	1	0.
157	Hyundai Verna Transform VTVT	0.551724	380000	0.355222	4	2	3	0
1540	Honda City i VTEC SV	0.689655	575000	0.026170	4	2	1	0.
1205	Maruti Swift Dzire VXI 1.2 BS IV	0.758621	620000	0.401961	4	2	1	0.
356	Honda City Corporate Edition	0.586207	540000	0.448701	4	2	3	0.
1361	Toyota Corolla Altis 1.8 J	0.482759	340000	0.364570	4	2	3	0
1200	Honda City 1.5 S MT	0.758621	675000	0.212773	4	2	1	0

In [185…

```
user_offroad = {
    "age": 34,
    "has_family": 1,
    "annual_km": 20000,
    "primary_use": "mixed",
```

```
    "drive_style": "normal",
    "budget_level": 0.55,
    "comfort_priority": 0.65,
    "performance_priority": 0.45,
    "eco_priority": 0.50,
    "space_need": 0.75,
    "reliability_priority": 0.70,
    "offroad_need": 0.80,
    "transmission_pref": "Automatic",
    "fuel_pref": "Diesel",
}
recommend_for_user_profile(user_offroad, top_n=10)
```

Out [185…

	name	year	selling_price	km_driven	fuel	transmission	owner	
362	Toyota Innova Crysta 2.8 GX AT 8S BSIV	0.793103	1800000	0.074783	2	1	1	0
1233	Toyota Fortuner 4x4 AT	0.724138	1750000	0.224350	2	1	1	0
36	Maruti Swift Dzire AMT ZDI	0.724138	650000	0.215003	2	1	3	0.
1158	Mahindra Scorpio VLX AT AIRBAG BSIV	0.517241	509999	0.434679	2	1	3	0
1254	Mahindra Scorpio VLS AT 2.2 mHAWK	0.551724	450000	0.425331	2	1	3	0.
209	Ford Endeavour 3.0L 4X4 AT	0.551724	975000	0.418171	2	1	3	0
451	Skoda Octavia Style Plus 2.0 TDI AT	0.827586	2600000	0.032718	2	1	1	0
305	Ford Endeavour 3.2 Titanium AT 4X4	0.724138	2280000	0.542180	2	1	3	0
1397	Ford Endeavour 2.2 Titanium AT 4X2	0.724138	2100000	0.378591	2	1	3	0
446	MG Hector Sharp DCT Dualtone	0.862069	1900000	0.000000	4	1	1	0

In [186…

```
user_premium = {
    "age": 42,
    "has_family": 0,
    "annual_km": 15000,
    "primary_use": "mixed",
    "drive_style": "normal",
```

```
    "budget_level": 0.85,
    "comfort_priority": 0.90,
    "performance_priority": 0.55,
    "eco_priority": 0.45,
    "space_need": 0.50,
    "reliability_priority": 0.75,
    "offroad_need": 0.10,
    "transmission_pref": "Automatic",
    "fuel_pref": "Petrol",
}
recommend_for_user_profile(user_premium, top_n=10)
```

Out [186…

	name	year	selling_price	km_driven	fuel	transmission	owner
1339	Audi RS3 Sedan	0.896552	5900000	0.093479	4	1	1
1601	BMW M3 Sedan	0.758621	5800000	0.149567	4	1	1
392	BMW M340i Sedan	0.862069	4600000	0.177611	4	1	3
814	Audi S3 Sedan	0.896552	4200000	0.126197	4	1	3
1343	Mercedes-AMG C63 S Sedan	0.758621	6800000	0.233698	4	1	3
592	Audi Q7 3.0 TDI Quattro Premium Plus	0.586207	1850000	0.308482	2	1	1
588	Audi Q7 3.0 TDI Quattro	0.655172	3000000	0.285112	2	1	1
586	Audi Q5 3.0 TDI Quattro	0.655172	1850000	0.337138	2	1	1
1460	Toyota Corolla GR Sport Turbo	0.896552	3800000	0.102827	4	1	1
1605	BMW M5 Competition	0.827586	9800000	0.084131	4	1	1

In [187…

```
user_high_mileage = {
    "age": 45,
    "has_family": 1,
    "annual_km": 32000,
    "primary_use": "daily",
    "drive_style": "calm",
    "budget_level": 0.60,
    "comfort_priority": 0.70,
    "performance_priority": 0.30,
    "eco_priority": 0.75,
    "space_need": 0.65,
    "reliability_priority": 0.85,
    "offroad_need": 0.15,
    "transmission_pref": "Automatic",
```

```
    "fuel_pref": "Diesel",
}
recommend_for_user_profile(user_high_mileage, top_n=10)
```

Out[187…

	name	year	selling_price	km_driven	fuel	transmission	owner	
362	Toyota Innova Crysta 2.8 GX AT 8S BSIV	0.793103	1800000	0.074783	2	1	1	0
1233	Toyota Fortuner 4x4 AT	0.724138	1750000	0.224350	2	1	1	0
36	Maruti Swift Dzire AMT ZDI	0.724138	650000	0.215003	2	1	3	0
1158	Mahindra Scorpio VLX AT AIRBAG BSIV	0.517241	509999	0.434679	2	1	3	0
1254	Mahindra Scorpio VLS AT 2.2 mHAWK	0.551724	450000	0.425331	2	1	3	0
209	Ford Endeavour 3.0L 4X4 AT	0.551724	975000	0.418171	2	1	3	0.
1397	Ford Endeavour 2.2 Titanium AT 4X2	0.724138	2100000	0.378591	2	1	3	0.
451	Skoda Octavia Style Plus 2.0 TDI AT	0.827586	2600000	0.032718	2	1	1	0
305	Ford Endeavour 3.2 Titanium AT 4X4	0.724138	2280000	0.542180	2	1	3	0
446	MG Hector Sharp DCT Dualtone	0.862069	1900000	0.000000	4	1	1	0.