Importy

In [1]:
```
from pathlib import Path
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
import joblib
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import FunctionTransformer, StandardScaler, OneHotEncode
from sklearn.preprocessing import StandardScaler as _SS

from sklearn.pipeline import Pipeline
from sklearn.dummy import DummyRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score


import os, json, uuid, time, math, random
from pathlib import Path
from sklearn.cluster import KMeans
import torch
from torch import nn
from torch.utils.data import TensorDataset, DataLoader
from torch.amp import autocast, GradScaler
scaler = GradScaler('cuda')
import wandb
from itertools import product

from sklearn.impute import SimpleImputer
import time
from copy import deepcopy
```

In [2]:
```
#cesta
CSV_PATH = Path(r"C:\Users\adria\PycharmProjects\pythonProject\ZNEUS\PROJEKT\houses
CSV_PATH
```

Out[2]:
```
WindowsPath('C:/Users/adria/PycharmProjects/pythonProject/ZNEUS/PROJEKT/houses.cs
v')
```

EDA - Data analysis

Load dataset

In [3]:
```
df = pd.read_csv(CSV_PATH)

print("Shape:", df.shape)
display(df.head(10))
```

```
Shape: (20640, 9)
```

	median_house_value	median_income	housing_median_age	total_rooms	total_bedrooms
0	452600.0	8.3252	41.0	880.0	129.0
1	358500.0	8.3014	21.0	7099.0	1106.0
2	352100.0	7.2574	52.0	1467.0	190.0
3	341300.0	5.6431	52.0	1274.0	235.0
4	342200.0	3.8462	52.0	1627.0	280.0
5	269700.0	4.0368	52.0	919.0	213.0
6	299200.0	3.6591	52.0	2535.0	489.0
7	241400.0	3.1200	52.0	3104.0	687.0
8	226700.0	2.0804	42.0	2555.0	665.0
9	261100.0	3.6912	52.0	3549.0	707.0

Dtypes, missing, duplicates

In [4]:

```
display(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   median_house_value  20640 non-null  float64
 1   median_income       20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20640 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   latitude            20640 non-null  float64
 8   longitude           20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
None
```

In [5]:

```
print("Dtypes, missing counts")
dtypes_missing = pd.DataFrame({
    "dtype": df.dtypes.astype(str),
    "missing_count": df.isna().sum(),
    "missing_rate": (df.isna().mean()).round(4),
    "unique_count": df.nunique(dropna=True)
}).sort_values("missing_count", ascending=False)
display(dtypes_missing)

dups = df.duplicated().sum()
print("Duplicated rows:", dups)
```

```
Dtypes, missing counts
```

	dtype	missing_count	missing_rate	unique_count
median_house_value	float64	0	0.0	3842
median_income	float64	0	0.0	12928
housing_median_age	float64	0	0.0	52
total_rooms	float64	0	0.0	5926
total_bedrooms	float64	0	0.0	1928
population	float64	0	0.0	3888
households	float64	0	0.0	1815
latitude	float64	0	0.0	862
longitude	float64	0	0.0	844

```
Duplicated rows: 0
```

Statistics for numeric columns

In [6]:
```
num = df.select_dtypes(include=[np.number])
if num.shape[1] > 0:
    display(num.describe().T)
else:
    print("No numeric columns found.")
```

	count	mean	std	min	25%	
median_house_value	20640.0	206855.816909	115395.615874	14999.0000	119600.0000	179700
median_income	20640.0	3.870671	1.899822	0.4999	2.5634	3
housing_median_age	20640.0	28.639486	12.585558	1.0000	18.0000	29
total_rooms	20640.0	2635.763081	2181.615252	2.0000	1447.7500	2127
total_bedrooms	20640.0	537.898014	421.247906	1.0000	295.0000	435
population	20640.0	1425.476744	1132.462122	3.0000	787.0000	1166
households	20640.0	499.539680	382.329753	1.0000	280.0000	409
latitude	20640.0	35.631861	2.135952	32.5400	33.9300	34
longitude	20640.0	-119.569704	2.003532	-124.3500	-121.8000	-118

In [7]:
```
maxv = df['median_house_value'].max()
print("Max value:", maxv, " Count:", (df['median_house_value']==maxv).sum())
df['is_censored'] = (df['median_house_value']==maxv).astype(int)
df['is_censored'].value_counts()
```

```
Max value: 500001.0  Count: 965
```

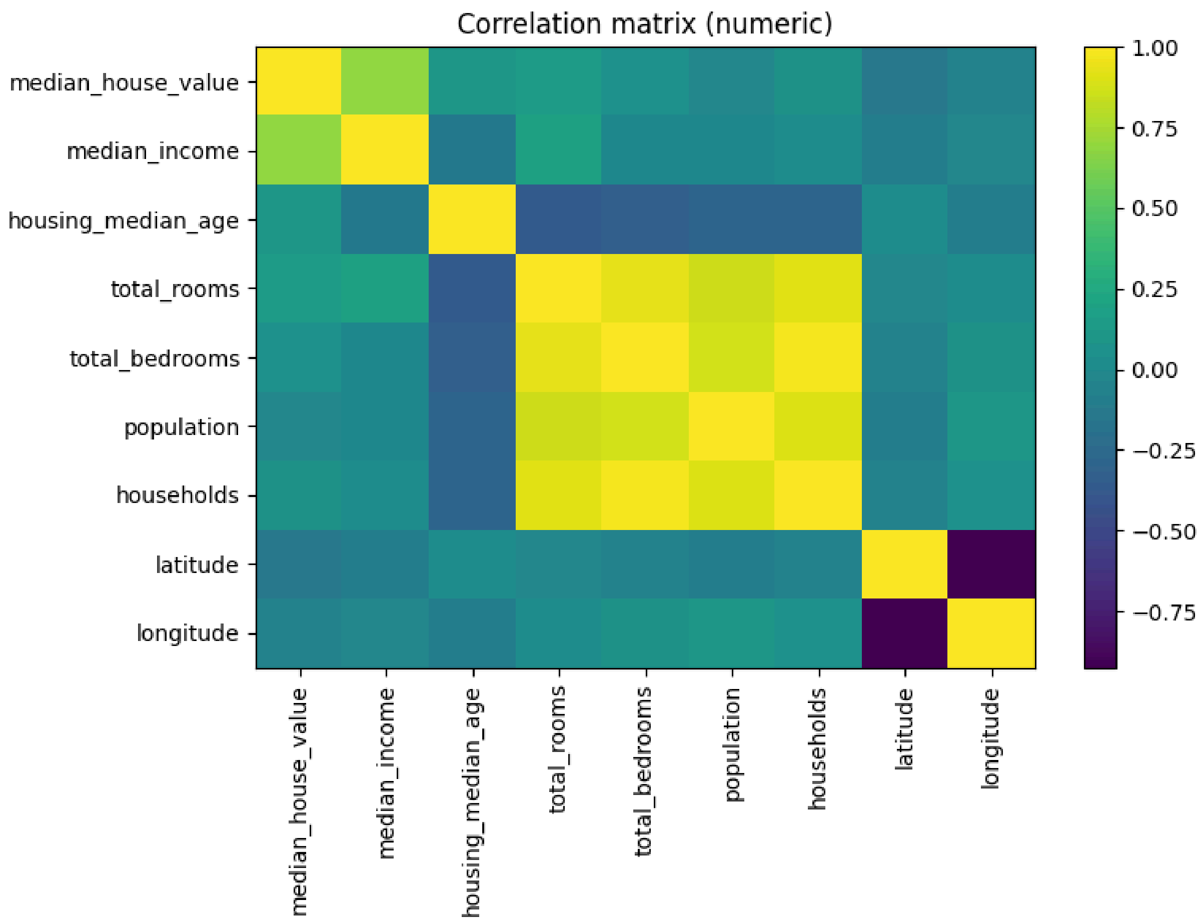
```
Out[7]: is_censored
0    19675
1      965
Name: count, dtype: int64
```

```
In [8]:
if num.shape[1] > 0:
    iqr = num.quantile(0.75) - num.quantile(0.25)
    range_ = num.max() - num.min()
    outlier_flag = (range_ / (iqr.replace(0, np.nan))).sort_values(ascending=False)
    print("\nTop features by range / IQR (may indicate heavy tails or outliers):")
    display(outlier_flag)
else:
    print("No numeric columns found.")
```

```
Top features by range / IQR (may indicate heavy tails or outliers):
population            38.037313
total_rooms           23.124835
households            18.710769
total_bedrooms        18.306818
median_income          6.651926
median_house_value     3.341960
housing_median_age     2.684211
longitude              2.649077
latitude               2.489418
dtype: float64
```

Correlation matrix for numeric features

```
In [9]:
num = df.select_dtypes(include=[np.number]).drop(columns=['is_censored'], errors='i

if num.shape[1] >= 2:
    corr = num.corr(numeric_only=True)
    plt.figure(figsize=(8,6))
    plt.imshow(corr, interpolation="nearest", aspect="auto")
    plt.colorbar()
    plt.xticks(range(len(corr.columns)), corr.columns, rotation=90)
    plt.yticks(range(len(corr.index)), corr.index)
    plt.title("Correlation matrix (numeric)")
    plt.tight_layout()
    plt.show()
else:
    print("Not enough numeric columns for correlation matrix.")
```



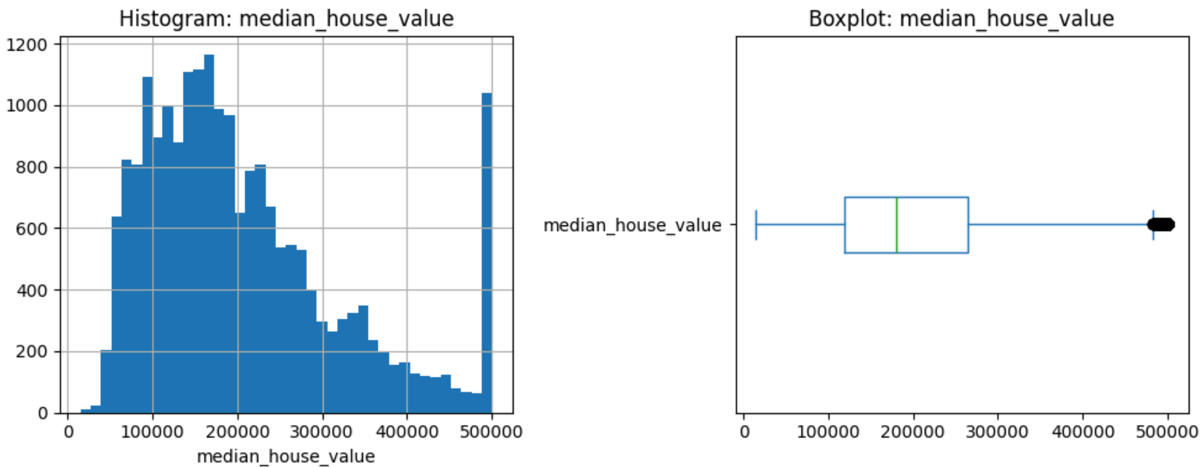
In [10]:
```
target = "median_house_value"
if target in corr.columns:
    target_corr = corr[target].drop(target).abs().sort_values(ascending=False)
    print("Top features by absolute correlation with target:")
    display(target_corr.head(10))
else:
    print("Target not in numeric columns for correlation.")
```

```
Top features by absolute correlation with target:
median_income         0.688075
latitude              0.144160
total_rooms           0.134153
housing_median_age    0.105623
households            0.065843
total_bedrooms        0.050594
longitude             0.045967
population            0.024650
Name: median_house_value, dtype: float64
```

Target distribution

In [11]:
```
plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
df[target].dropna().hist(bins=40)
plt.title(f"Histogram: {target}")
plt.xlabel(target)
```

```
plt.subplot(1,2,2)
df[target].dropna().plot.box(vert=False)
plt.title(f"Boxplot: {target}")

plt.tight_layout()
plt.show()
```



In [12]:
```
skew = num.skew().sort_values(ascending=False)
display(skew)
```

```
population            4.935858
total_rooms           4.147343
total_bedrooms        3.453073
households            3.410438
median_income         1.646657
median_house_value    0.977763
latitude              0.465953
housing_median_age    0.060331
longitude            -0.297801
dtype: float64
```

In [13]:
```
kurtosis = num.kurtosis().sort_values(ascending=False)
display(kurtosis)
```

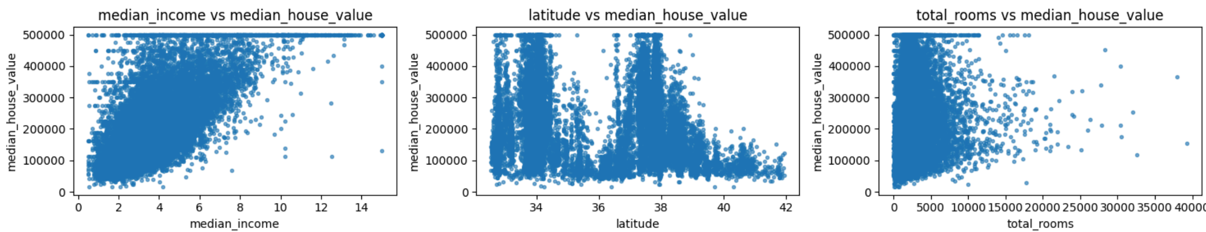
```
population            73.553116
total_rooms           32.630927
households            22.057988
total_bedrooms        21.923495
median_income          4.952524
median_house_value     0.327870
housing_median_age    -0.800629
latitude              -1.117760
longitude             -1.330152
dtype: float64
```

Scatter and Pair plots for top numeric features correlated with target

In [14]:
```
if target in num.columns:
    corr_with_target = num.corr()[target].abs().drop(target).sort_values(ascending=
    top_feats = corr_with_target.head(3).index.tolist()
    print("Top numeric features vs target:", top_feats)
```

```
    n = len(top_feats)
    if n > 0:
        plt.figure(figsize=(5*n,3))
        for i, f in enumerate(top_feats,1):
            plt.subplot(1,n,i)
            plt.scatter(df[f], df[target], s=8, alpha=0.6)
            plt.xlabel(f); plt.ylabel(target)
            plt.title(f"{f} vs {target}")
        plt.tight_layout()
        plt.show()
else:
    print("Target not numeric or no numeric features.")
```

```
Top numeric features vs target: ['median_income', 'latitude', 'total_rooms']
```

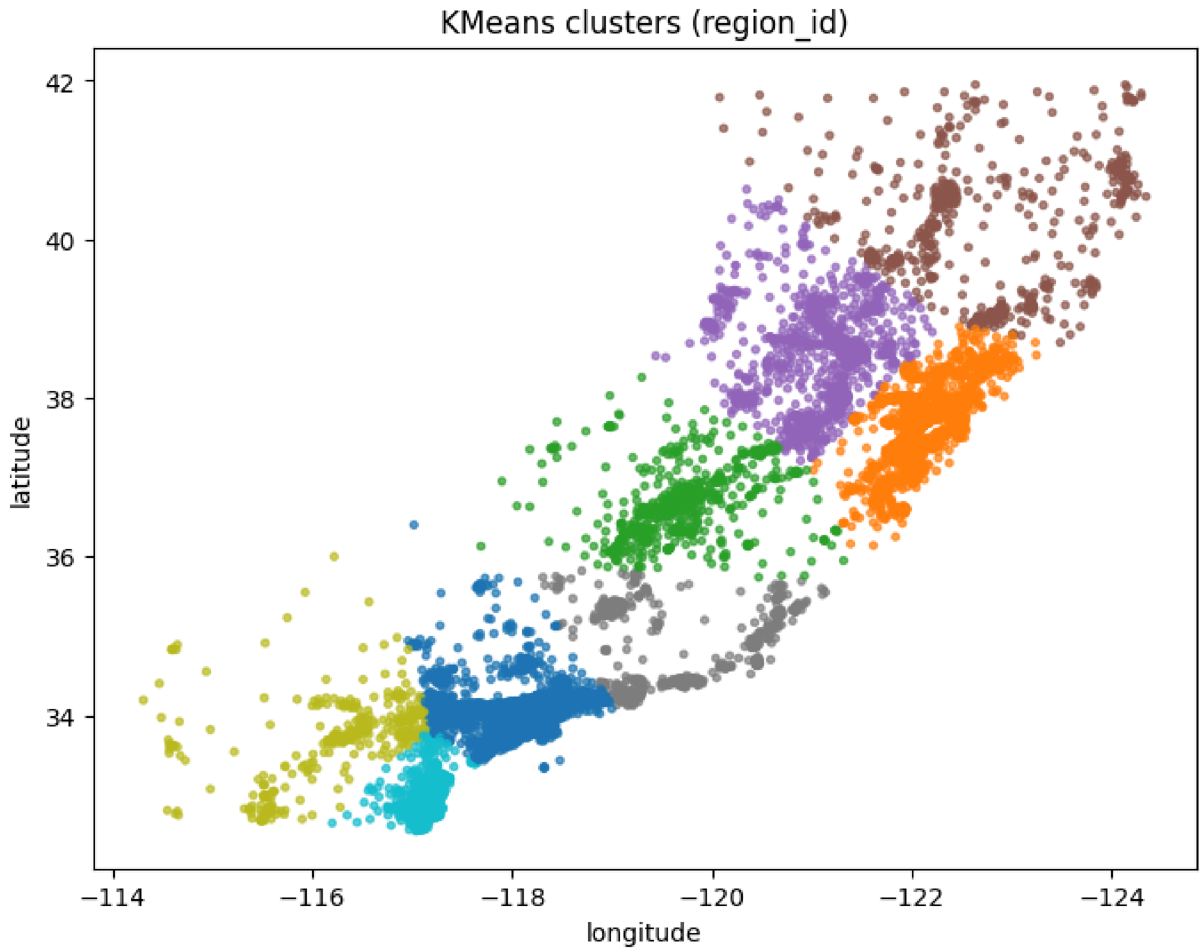


Region exploration

In [15]:
```
coords = df[['latitude','longitude']]
km = KMeans(n_clusters=8, random_state=0).fit(coords)
df['region_id'] = km.labels_
df.groupby('region_id')['median_house_value'].median().sort_values()
```

Out[15]:
```
region_id
2     76400.0
4     85800.0
6     89000.0
3    117800.0
7    169650.0
5    181600.0
0    198400.0
1    245100.0
Name: median_house_value, dtype: float64
```

In [16]:
```
plt.figure(figsize=(8,6))
plt.scatter(df['longitude'], df['latitude'], c=df['region_id'], s=8, cmap='tab10',
plt.gca().invert_xaxis()
plt.title("KMeans clusters (region_id)")
plt.xlabel("longitude"); plt.ylabel("latitude")
plt.show()
```



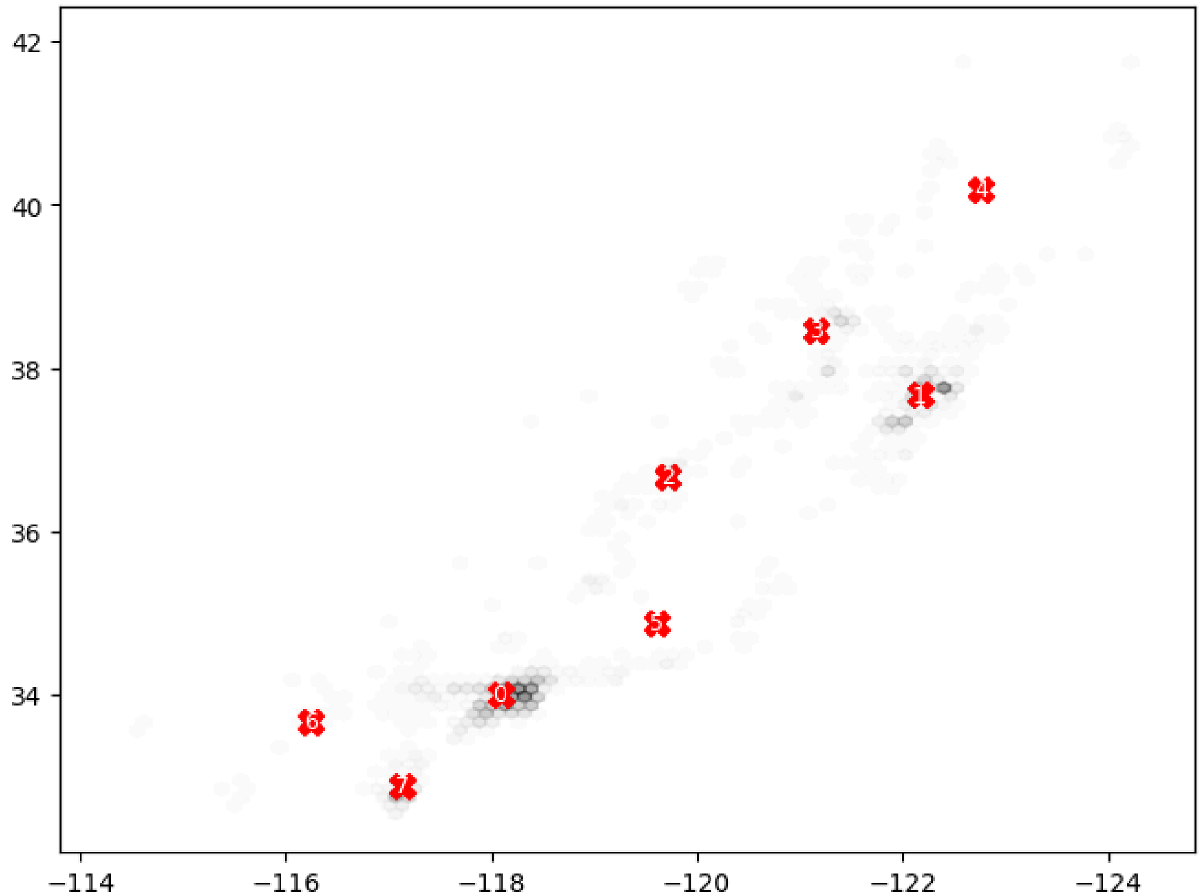
In [17]:
```
df.groupby('region_id', observed=False)['median_house_value'].agg(['count','median'
```

Out[17]:

region_id	count	median	mean
2	1117	76400.0	86213.249776
4	685	85800.0	92102.916788
6	474	89000.0	106898.529536
3	2203	117800.0	127250.976396
7	1678	169650.0	198141.446365
5	986	181600.0	191438.676471
0	8652	198400.0	229496.027624
1	4845	245100.0	262594.436739

In [18]:
```
centroids = km.cluster_centers_
plt.figure(figsize=(8,6))
plt.hexbin(df["longitude"], df["latitude"], gridsize=80, mincnt=1, cmap='Greys', al
plt.scatter(centroids[:,1], centroids[:,0], c='red', s=100, marker='X')
for i,(lon,lat) in enumerate(zip(centroids[:,1], centroids[:,0])):
```

```
    plt.text(lon, lat, str(i), color='white', fontsize=9, ha='center', va='center')
plt.gca().invert_xaxis()
plt.show()
```



Categorical check

In [19]:
```
categ = df.select_dtypes(include=["object","category"]).columns.tolist()
if not categ:
    print("No categorical columns found.")
else:
    for c in categ:
        print(f"\nColumn: {c} | Unique: {df[c].nunique()}")
        print(df[c].value_counts().head(5))
```

```
No categorical columns found.
```

EDA zhrnutie:

- **Veľkosť a čistota dát:** 20 640 riadkov, 9 stĺpcov. V EDA žiadne chýbajúce hodnoty a 0 úplných duplicitných riadkov — dáta sú kompletné a pripravené na ďalšiu analýzu.
- **Cieľ — `median_house_value`:**
  - mean ≈ **206 856**, median ≈ **179 700**, veľký rozptyl.
  - max = **500001.0**, počet pri maxime = **965**

- **Hlavné prediktory (lineárne):**
  - `median_income` má najsilnejšiu pozitívnu koreláciu s cenou (~**0.69**) — kľúčový prediktor.
  - Ďalej sú relevantné priestorové prvky (`latitude` / `longitude`) a štrukturálne metriky domu `total_rooms` ...
- **Outliery a šikmosť:**
  - Stĺpce `population` , `total_rooms` , `households` , `total_bedrooms` majú veľký `range / IQR` a vysoký skew → silné chvosty.
  - `median_house_value` skew ≈ **0.98** (pravostranný).
- **Vizualizácie a priestorový vzor:**
  - Scatter / pairplot potvrdili silný trend `median_income` vs cena a regionálne pásy podľa `latitude` .
  - Hexbin (longitude vs latitude) ukázal jasné **hotspoty**
- **Regionálne klastre (KMeans, k=8):**
  - KMeans vytvoril regiony s rôznymi mediánmi
  - Veľkosti klastrov sú nerovnomerné (niektoré stovky, iné tisícky riadkov) — pri použití v modeli zohľadni nerovnomernosť.
  - Dôležité: KMeans v EDA možno fitnúť na celom df len pre exploráciu

EXPERIMENTS 1-3

EXPERIMENT 1

Data preprocessing and normalization

In [20]:
```
CONFIG = {}
TARGET = "median_house_value"

EXCLUDE = {TARGET, "is_censored"}
if "region_id" in df.columns:
    EXCLUDE.add("region_id")

FEATURES_NUM = (
    df.drop(columns=[c for c in EXCLUDE if c in df.columns], errors="ignore")
      .select_dtypes(include=[np.number])
      .columns.tolist()
)

CONFIG["features_num"] = FEATURES_NUM
```

In [21]:
```
print(f"Target: {TARGET}")
print(f"Počet numerických features: {len(FEATURES_NUM)}")
```

```
print("Features:", FEATURES_NUM)
```

```
Target: median_house_value
Počet numerických features: 8
Features: ['median_income', 'housing_median_age', 'total_rooms', 'total_bedrooms',
'population', 'households', 'latitude', 'longitude']
```

In [22]:
```
def suggest_log_cols(frame: pd.DataFrame, cols: list[str], skew_threshold: float =
    skew_vals = frame[cols].skew(numeric_only=True)
    return skew_vals[skew_vals.abs() >= skew_threshold].index.tolist()

def make_preprocess(feature_cols: list[str], log_cols: list[str] | None = None):
    if log_cols is None:
        log_cols = []
    other_cols = [c for c in feature_cols if c not in log_cols]

    col_tf = ColumnTransformer(
        transformers=[
            ("log", FunctionTransformer(np.log1p, validate=False), log_cols),
            ("num", "passthrough", other_cols),
        ],
        remainder="drop"
    )
    preprocess = Pipeline([
        ("cols", col_tf),
        ("scaler", StandardScaler()),
    ])
    return preprocess
```

In [23]:
```
LOG_COLS_SUGGESTED = suggest_log_cols(df, FEATURES_NUM, skew_threshold=1.0)
print("Návrh log1p stĺpcov (na celej vzorke):", LOG_COLS_SUGGESTED)
```

```
Návrh log1p stĺpcov (na celej vzorke): ['median_income', 'total_rooms', 'total_bedro
oms', 'population', 'households']
```

Čo som spravil

- Vybral som 8 numerických stĺpcov (bez targetu/cenzúry).
- Na stĺpce s |skew| ≥ 1 som aplikoval `log1p`, potom `StandardScaler`.
- Preprocess som **fitoval len na TRAIN** a použil na VAL/TEST (bez leakage).

Výsledky

- Kontroly NaN/Inf ok, rozmery konzistentné.

Interpretácia

- `log1p` zmiernil dlhé chvosty a zlepšil stabilitu tréningu MLP.

Data split

In [24]:
```
SEED = 42
TEST_SIZE = 0.10
VAL_SIZE  = 0.10
```

```
N_BINS     = 10

rng = np.random.RandomState(SEED)
```

In [25]:
```
X_all = df[FEATURES_NUM].copy()
y_all = df[TARGET].to_numpy()

y_bins_all = pd.qcut(y_all, q=N_BINS, labels=False, duplicates="drop")

X_trval, X_test, y_trval, y_test, bins_trval, bins_test = train_test_split(
    X_all, y_all, y_bins_all,
    test_size=TEST_SIZE, random_state=SEED, stratify=y_bins_all
)

val_rel = VAL_SIZE / (1.0 - TEST_SIZE)
bins_trval_local = pd.qcut(y_trval, q=N_BINS, labels=False, duplicates="drop")

X_train, X_val, y_train, y_val = train_test_split(
    X_trval, y_trval,
    test_size=val_rel, random_state=SEED, stratify=bins_trval_local
)

print(f"Train: {X_train.shape},  Val: {X_val.shape},  Test: {X_test.shape}")
```

```
Train: (16512, 8),  Val: (2064, 8),  Test: (2064, 8)
```

In [26]:
```
def _brief_stats(name, y):
    return pd.Series({
        "n":    len(y),
        "mean": float(np.mean(y)),
        "std":  float(np.std(y)),
        "min":  float(np.min(y)),
        "25%":  float(np.quantile(y, 0.25)),
        "50%":  float(np.quantile(y, 0.50)),
        "75%":  float(np.quantile(y, 0.75)),
        "max":  float(np.max(y)),
    }, name=name)
```

In [27]:
```
display(pd.concat([
    _brief_stats("train", y_train),
    _brief_stats("val",   y_val),
    _brief_stats("test",  y_test),
], axis=1))
```

	train	val	test
n	16512.000000	2064.000000	2064.000000
mean	206859.070797	207094.135659	206591.467054
std	115428.240230	115759.619132	114739.638679
min	14999.000000	22500.000000	14999.000000
25%	119400.000000	120950.000000	121225.000000
50%	179700.000000	179700.000000	179750.000000
75%	264700.000000	264825.000000	265350.000000
max	500001.000000	500001.000000	500001.000000

Čo som spravil

- Stratifikoval som podľa **kvantilov cieľa** a rozdelil **Train/Val/Test = 80/10/10**.

Výsledky

- Tvary ~ **Train (16.5k, 8)**, **Val (2.1k, 8)**, **Test (2.1k, 8)**.

Interpretácia

- Udržal som distribúciu cieľa naprieč setmi

Configuration

In [28]:
```
CONFIG = {
    "seed": SEED,
    "target": TARGET,
    "data_split": {
        "test_size": TEST_SIZE,
        "val_size": VAL_SIZE,
        "strat_bins": N_BINS,
    },
    "preprocess": {
        "scaler": "standard",
        "auto_log_skew": True,
        "skew_threshold": 1.0,
        "manual_log_cols": [],
    },
    "features": FEATURES_NUM,
}
```

In [29]:
```
if CONFIG["preprocess"]["auto_log_skew"]:
    log_cols_final = suggest_log_cols(
        X_train, CONFIG["features"], CONFIG["preprocess"]["skew_threshold"]
    )
else:
```

```
    log_cols_final = [c for c in CONFIG["preprocess"]["manual_log_cols"] if c in CO

CONFIG["preprocess"]["log_cols"] = log_cols_final
print("log_cols (z TRAIN):", CONFIG["preprocess"]["log_cols"])
```

```
log_cols (z TRAIN): ['median_income', 'total_rooms', 'total_bedrooms', 'population',
'households']
```

In [30]:

```
cfg_small = {
    "preprocess": CONFIG["preprocess"],
    "data_split": CONFIG.get("data_split"),
    "n_features": len(CONFIG.get("features", [])),
    "features_head": CONFIG.get("features", [])[:10],
}
print(json.dumps(cfg_small, ensure_ascii=False, indent=2))
```


```
{
  "preprocess": {
    "scaler": "standard",
    "auto_log_skew": true,
    "skew_threshold": 1.0,
    "manual_log_cols": [],
    "log_cols": [
      "median_income",
      "total_rooms",
      "total_bedrooms",
      "population",
      "households"
    ]
  },
  "data_split": {
    "test_size": 0.1,
    "val_size": 0.1,
    "strat_bins": 10
  },
  "n_features": 8,
  "features_head": [
    "median_income",
    "housing_median_age",
    "total_rooms",
    "total_bedrooms",
    "population",
    "households",
    "latitude",
    "longitude"
  ]
}
```


Čo som spravil

- Založil som centralizovaný `CONFIG` (seed, features, auto výber log1p, parametre splitu).

Výsledky

- Jedno miesto pre celú pipeline.

Interpretácia

- Znižuje riziko chýb a zjednodušuje replikáciu.

Experiment tracking

In [31]:
```
EXP_HISTORY = []

def log_experiment_mem(params: dict, metrics: dict, notes: str = ""):
    run = {
        "run_id": str(uuid.uuid4())[:8],
        "timestamp": int(time.time()),
        "seed": CONFIG["seed"],
        "notes": notes,
        **{f"p_{k}": v for k, v in params.items()},
        **{f"m_{k}": v for k, v in metrics.items()},
    }
    EXP_HISTORY.append(run)
    return run
```

In [32]:
```
preprocess = make_preprocess(CONFIG["features"], CONFIG["preprocess"]["log_cols"])

Xtr = preprocess.fit_transform(X_train)
Xva = preprocess.transform(X_val)
Xte = preprocess.transform(X_test)

baseline = DummyRegressor(strategy="median")
baseline.fit(Xtr, y_train)

def reg_metrics(y_true, y_pred):
    rmse = float(np.sqrt(mean_squared_error(y_true, y_pred)))
    mae  = float(mean_absolute_error(y_true, y_pred))
    return {"rmse": rmse, "mae": mae}
```

In [33]:
```
m_tr = reg_metrics(y_train, baseline.predict(Xtr))
m_va = reg_metrics(y_val,   baseline.predict(Xva))
m_te = reg_metrics(y_test,  baseline.predict(Xte))

display(pd.DataFrame({"train": m_tr, "val": m_va, "test": m_te}))
```

	train	val	test
rmse	118580.326232	118956.832885	117848.783127
mae	88360.015686	88658.379845	88002.807171

Čo som spravil

- Spustil som `DummyRegressor(strategy="median")` ako nulovú referenciu.

Výsledky (EUR)

- **RMSE ~118–119k**, **MAE ~88k** (Val ≈ Test).

Interpretácia

- Spodná hranica výkonu pre porovnanie.

Experiment

In [34]:
```
DEV = torch.device("cuda:0")

SEED = int(CONFIG.get("seed", 42))
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.benchmark = True

try:
    torch.set_float32_matmul_precision("high")
except Exception:
    pass
```

In [35]:
```
WANDB_ENTITY = None
WANDB_PROJECT = "EXPERIMENTS"
WANDB_GROUP = "EXP1-baseline"
os.environ["WANDB_SILENT"] = "true"

print(DEV, "n_features:", Xtr.shape[1])
```

```
cuda:0 n_features: 8
```

In [36]:
```
class ResidualBlock(nn.Module):
    def __init__(self, dim, hidden=None, batchnorm=True, dropout=0.0):
        super().__init__()
        h = hidden if hidden is not None else max(dim // 2, 16)
        self.bn1  = nn.BatchNorm1d(dim) if batchnorm else nn.Identity()
        self.fc1  = nn.Linear(dim, h)
        self.act  = nn.ReLU()
        self.bn2  = nn.BatchNorm1d(h) if batchnorm else nn.Identity()
        self.drop = nn.Dropout(dropout) if dropout > 0 else nn.Identity()
        self.fc2  = nn.Linear(h, dim)

    def forward(self, x):
        z = self.bn1(x)
        z = self.fc1(z); z = self.act(z)
        z = self.bn2(z); z = self.drop(z)
        z = self.fc2(z)
        return x + z
```

In [37]:
```
class TabularMLP(nn.Module):
    def __init__(self, in_dim, hidden_layers=(128,64,32),
                 batchnorm=True, dropout=0.0,
                 residual=False, bottleneck=False):
        super().__init__()
        dims = [in_dim] + list(hidden_layers)
```

```python
        if bottleneck and len(hidden_layers) >= 2:
            down = list(hidden_layers)
            up   = list(hidden_layers[:-1])[::-1]
            dims = [in_dim] + down + up

        layers = []
        for i in range(len(dims)-1):
            inp, out = dims[i], dims[i+1]
            layers.append(nn.Linear(inp, out))
            if batchnorm: layers.append(nn.BatchNorm1d(out))
            layers.append(nn.ReLU())
            if dropout > 0: layers.append(nn.Dropout(dropout))
            if residual and out >= 16:
                layers.append(ResidualBlock(out, batchnorm=batchnorm, dropout=dropo

        self.backbone = nn.Sequential(*layers)
        self.head = nn.Linear(dims[-1], 1)

    def forward(self, x):
        return self.head(self.backbone(x)).squeeze(1)
```

In [38]:
```python
SUPPORTS_BF16 = getattr(torch.cuda, "is_bf16_supported", lambda: False)()
AMP_DTYPE = torch.bfloat16 if SUPPORTS_BF16 else torch.float16

def make_loaders(Xtr, ytr, Xva, yva, batch_size=512):
    Xtr_t = torch.tensor(Xtr, dtype=torch.float32)
    ytr_t = torch.tensor(ytr, dtype=torch.float32)
    Xva_t = torch.tensor(Xva, dtype=torch.float32)
    yva_t = torch.tensor(yva, dtype=torch.float32)
    tr = DataLoader(TensorDataset(Xtr_t, ytr_t), batch_size=batch_size, shuffle=Tru
    va = DataLoader(TensorDataset(Xva_t, yva_t), batch_size=batch_size, shuffle=Fal
    return tr, va
```

In [39]:
```python
_y_scaler = StandardScaler().fit(y_train.reshape(-1,1))
y_train_s = _y_scaler.transform(y_train.reshape(-1,1)).ravel()
y_val_s   = _y_scaler.transform(y_val.reshape(-1,1)).ravel()
y_test_s  = _y_scaler.transform(y_test.reshape(-1,1)).ravel()

def _denorm(v):
    return _y_scaler.inverse_transform(np.asarray(v).reshape(-1,1)).ravel()
```

In [40]:
```python
def reg_metrics_true_units(y_true, y_pred):
    yt = np.asarray(y_true).ravel()
    yp = np.asarray(y_pred).ravel()
    rmse = float(np.sqrt(np.mean((yt - yp) ** 2)))
    mae  = float(np.mean(np.abs(yt - yp)))
    ss_res = float(np.sum((yt - yp) ** 2))
    ss_tot = float(np.sum((yt - np.mean(yt)) ** 2))
    r2 = float(1 - ss_res / (ss_tot + 1e-12))
    return {"rmse": rmse, "mae": mae, "r2": r2}
```

In [41]:
```python
def train_epoch(model, loader, opt, loss_fn, grad_clip=None, scaler=None):
    model.train()
    losses = []
```

```python
    for xb, yb in loader:
        xb = xb.to(DEV, non_blocking=True); yb = yb.to(DEV, non_blocking=True)
        opt.zero_grad(set_to_none=True)
        with autocast(device_type='cuda', dtype=AMP_DTYPE):
            pred = model(xb)
            loss = loss_fn(pred, yb)
        if scaler is not None:
            scaler.scale(loss).backward()
            if grad_clip is not None:
                scaler.unscale_(opt)
                nn.utils.clip_grad_norm_(model.parameters(), grad_clip)
            scaler.step(opt); scaler.update()
        else:
            loss.backward()
            if grad_clip is not None:
                nn.utils.clip_grad_norm_(model.parameters(), grad_clip)
            opt.step()
        losses.append(loss.item())
    return float(np.mean(losses))
```

In [42]:
```python
@torch.no_grad()
def eval_epoch(model, loader, loss_fn):
    model.eval()
    losses = []
    y_true_s = []
    y_pred_s = []
    for xb, yb in loader:
        xb = xb.to(DEV, non_blocking=True); yb = yb.to(DEV, non_blocking=True)
        with autocast(device_type='cuda', dtype=AMP_DTYPE):
            pred = model(xb)
            loss = loss_fn(pred, yb)
        losses.append(loss.item())
        y_true_s.append(yb.float().cpu().numpy())
        y_pred_s.append(pred.float().cpu().numpy())

    y_true_s = np.concatenate(y_true_s)
    y_pred_s = np.concatenate(y_pred_s)
    return (float(np.mean(losses)),
            reg_metrics_true_units(_denorm(y_true_s), _denorm(y_pred_s)),
            (_denorm(y_true_s), _denorm(y_pred_s)))
```

In [43]:
```python
DEFAULT_CFG = dict(
    seed=SEED,
    hidden_layers=[128, 64, 32],
    batchnorm=True,
    dropout=0.10,
    residual=False,
    bottleneck=True,
    optimizer="adam",
    lr=1e-3,
    weight_decay=1e-4,
    batch_size=1024,
    epochs=200,
    patience=20,
```

```python
    grad_clip=1.0
)
```

In [44]:
```python
def _init_experiment(cfg, Xtr, ytr_s, Xva, yva_s, wandb_tags=None, run_name=None):
    tr_loader, va_loader = make_loaders(Xtr, ytr_s, Xva, yva_s, batch_size=cfg["bat

    model = TabularMLP(in_dim=Xtr.shape[1],
                       hidden_layers=tuple(cfg["hidden_layers"]),
                       batchnorm=cfg["batchnorm"], dropout=cfg["dropout"],
                       residual=cfg["residual"], bottleneck=cfg["bottleneck"]).to(D

    if cfg["optimizer"] == "adam":
        opt = torch.optim.Adam(model.parameters(), lr=cfg["lr"], weight_decay=cfg["
    elif cfg["optimizer"] == "rmsprop":
        opt = torch.optim.RMSprop(model.parameters(), lr=cfg["lr"], weight_decay=cf
    else:
        opt = torch.optim.SGD(model.parameters(), lr=cfg["lr"], momentum=0.9, neste
                              weight_decay=cfg["weight_decay"])

    loss_fn = nn.MSELoss()
    sched = torch.optim.lr_scheduler.ReduceLROnPlateau(opt, mode="min", factor=0.5,
    scaler = GradScaler('cuda') if AMP_DTYPE == torch.float16 else None

    init_kwargs = dict(project=WANDB_PROJECT, group=WANDB_GROUP, name=run_name, con
    run = wandb.init(**init_kwargs)

    return model, opt, loss_fn, sched, scaler, tr_loader, va_loader, run
```

In [45]:
```python
def _train_with_early_stopping(model, opt, loss_fn, sched, scaler, tr_loader, va_lo
    best_val = float("inf")
    best_state = None
    patience_left = cfg["patience"]
    history = []

    for epoch in range(1, cfg["epochs"] + 1):
        tr_loss = train_epoch(model, tr_loader, opt, loss_fn, grad_clip=cfg["grad_c
        va_loss, va_m, _ = eval_epoch(model, va_loader, loss_fn)
        sched.step(va_loss)

        history.append({"epoch": epoch, "train_loss_s": tr_loss, "val_loss_s": va_l
                        **{f"val_{k}": v for k, v in va_m.items()}})

        wandb.log({
            "epoch": epoch,
            "train_loss_scaled": tr_loss,
            "val_loss_scaled": va_loss,
            "val_rmse": va_m["rmse"],
            "val_mae":  va_m["mae"],
            "val_r2":   va_m["r2"],
            "lr": opt.param_groups[0]["lr"],
        }, step=epoch)

        if va_loss < best_val - 1e-7:
            best_val = va_loss
            patience_left = cfg["patience"]
```

```
            best_state = {k: v.detach().cpu().clone() for k, v in model.state_dict(
        else:
            patience_left -= 1
            if patience_left <= 0:
                break

    return history, best_state
```

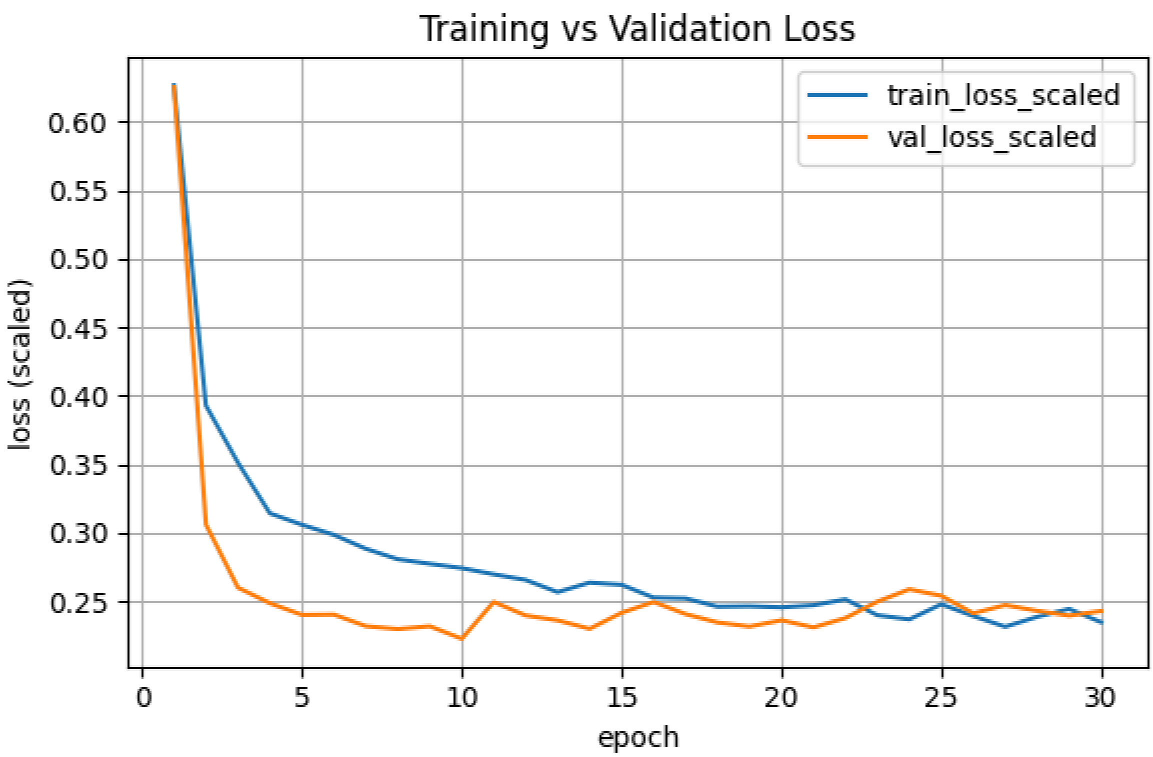
In [46]:
```
def _full_eval_and_log(model, cfg, Xtr, ytr_s, Xva, yva_s, Xte, yte_s, run):
    def _full_eval(X, y_s):
        loader = DataLoader(TensorDataset(torch.tensor(X, dtype=torch.float32),
                                          torch.tensor(y_s, dtype=torch.float32)),
                            batch_size=cfg["batch_size"], shuffle=False, pin_memory
        _, m, (yt, yp) = eval_epoch(model, loader, nn.MSELoss())
        return m, (yt, yp)

    tr_m, _ = _full_eval(Xtr, ytr_s)
    va_m, _ = _full_eval(Xva, yva_s)
    te_m, (yt, yp) = _full_eval(Xte, yte_s)

    run.summary.update({
        "train_rmse": tr_m["rmse"], "train_mae": tr_m["mae"], "train_r2": tr_m["r2"
        "val_rmse":   va_m["rmse"], "val_mae":   va_m["mae"], "val_r2":   va_m["r2"
        "test_rmse":  te_m["rmse"], "test_mae":  te_m["mae"], "test_r2":  te_m["r2"
        "epochs_run": len(history) if False else None
    })

    return {"train": tr_m, "val": va_m, "test": te_m}, (yt, yp)
```

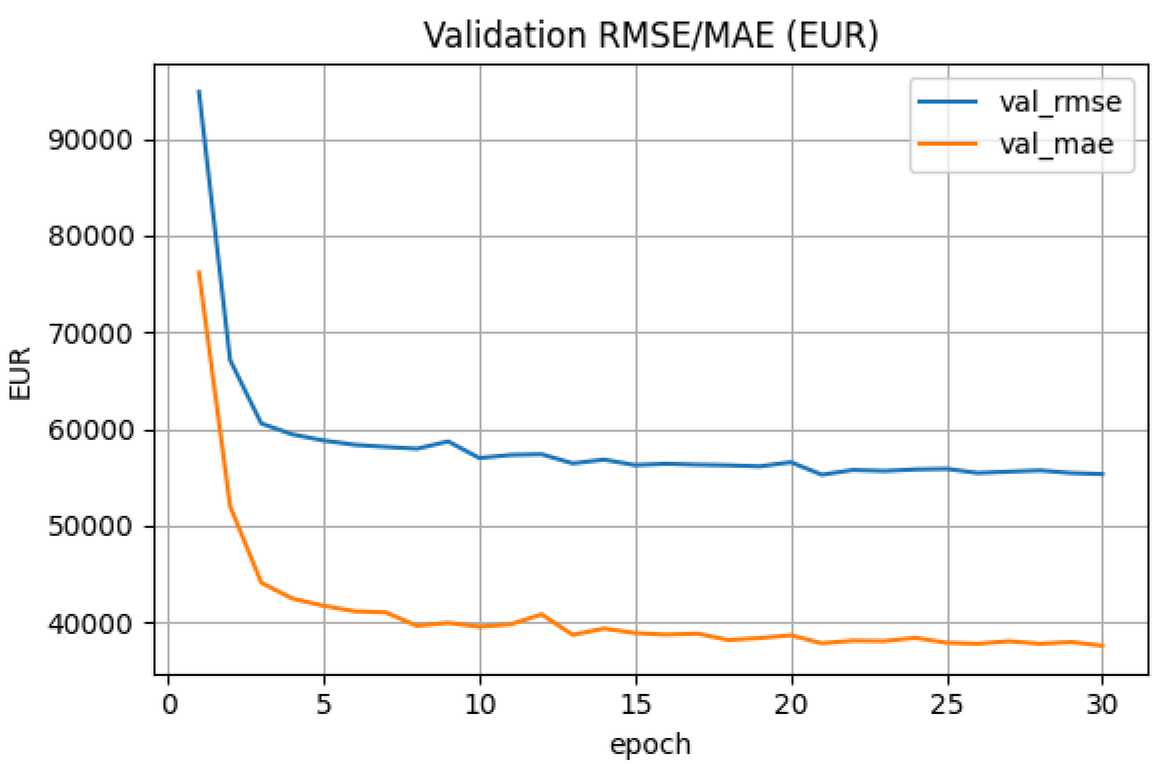
In [47]:
```
def run_experiment(cfg, Xtr, ytr_s, Xva, yva_s, Xte, yte_s, wandb_tags=None, run_na
    model, opt, loss_fn, sched, scaler, tr_loader, va_loader, run = _init_experimen
        cfg, Xtr, ytr_s, Xva, yva_s, wandb_tags=wandb_tags, run_name=run_name
    )

    history, best_state = _train_with_early_stopping(model, opt, loss_fn, sched, sc

    if best_state is not None:
        model.load_state_dict(best_state)

    res_dict, _ = _full_eval_and_log(model, cfg, Xtr, ytr_s, Xva, yva_s, Xte, yte_s

    run.finish()
    return model, history, res_dict
```

In [48]:
```
model_baseline, hist_baseline, res_baseline = run_experiment(
    DEFAULT_CFG,
    Xtr, y_train_s, Xva, y_val_s, Xte, y_test_s,
    wandb_tags=["baseline","bn","dropout","bottleneck"],
    run_name="EXPERIMENT1-baseline"
)

hist_df = pd.DataFrame(hist_baseline)
```

In [49]:
```
plt.figure(figsize=(6,4))
plt.plot(hist_df["epoch"], hist_df["train_loss_s"], label="train_loss_scaled")
```

```
plt.plot(hist_df["epoch"], hist_df["val_loss_s"],   label="val_loss_scaled")
plt.xlabel("epoch"); plt.ylabel("loss (scaled)"); plt.title("Training vs Validation
plt.legend(); plt.grid(True); plt.tight_layout(); plt.show()

plt.figure(figsize=(6,4))
plt.plot(hist_df["epoch"], hist_df["val_rmse"], label="val_rmse")
plt.plot(hist_df["epoch"], hist_df["val_mae"],  label="val_mae")
plt.xlabel("epoch"); plt.ylabel("EUR"); plt.title("Validation RMSE/MAE (EUR)")
plt.legend(); plt.grid(True); plt.tight_layout(); plt.show()
```





In [50]:
```python
print(pd.DataFrame(res_baseline).round(4))
```

```
            train         val        test
rmse   54497.3398  57005.7695  57039.6641
mae    38448.7500  39567.6328  39544.8516
r2         0.7771      0.7575      0.7529
```

Čo som spravil

- MLP `[256,128,64]`, **BatchNorm**, **Dropout ~0.10**, **bottleneck**.
- Optimalizácia: **Adam (LR≈1e-3)**, `ReduceLROnPlateau`, **early stopping**, AMP.

Výsledky (EUR)

- Train **~54k**, Val **~57k / ~40k MAE / R^2 ~0.75–0.76**, Test **~57k / ~40k MAE / R^2 ~0.75**.

Interpretácia

- Val ≈ Test → slušná generalizácia; strop určuje množstvo informácie vo features.

Hyperparameter search (grid/random) / sweep

In [51]:
```python
search_space = {
    "hidden_layers": [
        [256,128,64],
        [128,64,32],
        [256,128,64,32],
        [128,64,32,64,128],
    ],
    "dropout":      [0.00, 0.05, 0.10, 0.20, 0.30],
    "batchnorm":    [True, False],
    "residual":     [False, True],
    "bottleneck":   [False, True],
    "optimizer":    ["adam","rmsprop","sgd"],
    "lr":           [3e-4, 1e-3],
    "weight_decay": [0.0, 1e-5, 1e-4, 1e-3],
    "batch_size":   [512, 1024, 2048],
    "patience":     [10, 20, 30],
}
WANDB_GROUP = "EXP1-random"

def pick(k):
    return random.choice(search_space[k])

N_TRIALS = 16
random.seed(42)
```

In [52]:
```python
results = []
best = None

for t in range(1, N_TRIALS + 1):
    cfg = DEFAULT_CFG |{
        "hidden_layers": pick("hidden_layers"),
```

```
        "dropout":       pick("dropout"),
        "batchnorm":     pick("batchnorm"),
        "residual":      pick("residual"),
        "bottleneck":    pick("bottleneck"),
        "optimizer":     pick("optimizer"),
        "lr":            pick("lr"),
        "weight_decay":  pick("weight_decay"),
        "batch_size":    pick("batch_size"),
        "patience":      pick("patience"),
        "seed":          random.randint(1, 10_000),
    }

    _, hist_i, res_i = run_experiment(
        cfg,
        Xtr, y_train_s, Xva, y_val_s, Xte, y_test_s,
        wandb_tags=["random-search","EXP1"],
        run_name=f"EXPERIMENT1-rand-{t:02d}"
    )

    row = {
        "trial": t,
        "val_rmse":  res_i["val"]["rmse"],  "val_mae":  res_i["val"]["mae"],  "val_
        "test_rmse": res_i["test"]["rmse"], "test_mae": res_i["test"]["mae"], "test
        "cfg": cfg
    }
    results.append(row)
    if best is None or row["val_rmse"] < best["val_rmse"]:
        best = row

res_df = pd.DataFrame(results).sort_values("test_rmse").reset_index(drop=True)
```

In [53]:

```
display(res_df[["trial","val_rmse","val_mae","val_r2","test_rmse","test_mae","test_
```

	trial	val_rmse	val_mae	val_r2	test_rmse	test_mae	test_r2
0	8	54791.94	36329.73	0.78	55026.29	36033.54	0.77
1	13	56024.22	38416.66	0.77	56216.36	38533.17	0.76
2	4	56549.23	37687.66	0.76	56517.07	37022.33	0.76
3	5	56928.77	39401.02	0.76	57257.67	39558.74	0.75
4	6	57498.70	38930.01	0.75	57413.57	38688.31	0.75
5	2	57740.38	39894.01	0.75	57926.43	39826.64	0.75
6	12	57604.21	39773.11	0.75	58262.83	39658.39	0.74
7	3	57445.81	39754.99	0.75	58305.04	39170.13	0.74
8	9	58617.56	40584.36	0.74	58840.70	40284.08	0.74
9	10	59225.02	41836.99	0.74	59555.50	41653.15	0.73
10	1	59660.49	42130.79	0.73	59867.79	41748.04	0.73
11	14	60425.13	42679.32	0.73	61060.25	42353.48	0.72
12	16	61474.27	43886.78	0.72	61827.71	43887.54	0.71
13	7	63054.42	44005.96	0.70	63059.09	43192.93	0.70
14	15	64632.85	46823.05	0.69	65196.39	47210.70	0.68
15	11	115792.25	90481.38	-0.00	114748.84	89724.23	-0.00

In [113…

```
print("\nNajlepší trial (podľa test_rmse):")
print(res_df.iloc[0])

best_cfg = res_df.iloc[0]["cfg"]
```

```
Najlepší trial (podľa test_rmse):
trial                                                        8
val_rmse                                          54791.941406
val_mae                                           36329.730469
val_r2                                                0.775963
test_rmse                                         55026.285156
test_mae                                          36033.542969
test_r2                                               0.770008
cfg          {'seed': 8180, 'hidden_layers': [128, 64, 32],...
Name: 0, dtype: object
```

In [55]:

```
grid = {
    "hidden_layers": [[256,128,64],[128,64,32]],
    "dropout": [0.05, 0.10],
    "optimizer": ["adam","rmsprop"],
    "lr": [3e-4, 1e-3],
    "weight_decay": [1e-4],
}
WANDB_GROUP = "EXP1-grid"
```

```python
grid_keys = list(grid.keys())
grid_vals = list(grid.values())

grid_results = []
i = 0
for values in product(*grid_vals):
    i += 1
    cfg = DEFAULT_CFG | {k: v for k, v in zip(grid_keys, values)}
    _, _, res_i = run_experiment(
        cfg, Xtr, y_train_s, Xva, y_val_s, Xte, y_test_s,
        wandb_tags=["grid-search"], run_name=f"EXPERIMENT1-grid-{i:02d}"
    )
    grid_results.append({"i": i, "cfg": cfg, "val_rmse": res_i["val"]["rmse"], "tes
```

In [56]:

```python
pd.DataFrame(grid_results).sort_values("test_rmse").head(10)
```

Out[56]:

	i	cfg	val_rmse	test_rmse
7	8	{'seed': 42, 'hidden_layers': [256, 128, 64], ...	54629.953125	54573.812500
13	14	{'seed': 42, 'hidden_layers': [128, 64, 32], '...	55659.156250	55346.910156
9	10	{'seed': 42, 'hidden_layers': [128, 64, 32], '...	54728.906250	55499.867188
0	1	{'seed': 42, 'hidden_layers': [256, 128, 64], ...	55478.167969	55684.269531
5	6	{'seed': 42, 'hidden_layers': [256, 128, 64], ...	55481.292969	55721.011719
2	3	{'seed': 42, 'hidden_layers': [256, 128, 64], ...	55649.648438	55829.703125
6	7	{'seed': 42, 'hidden_layers': [256, 128, 64], ...	56063.800781	56844.382812
8	9	{'seed': 42, 'hidden_layers': [128, 64, 32], '...	57240.386719	57116.785156
10	11	{'seed': 42, 'hidden_layers': [128, 64, 32], '...	57204.406250	57190.980469
4	5	{'seed': 42, 'hidden_layers': [256, 128, 64], ...	57705.449219	57651.160156

Hyperparameter search (random)

Čo som spravil

- Spustil som 16 náhodných behov cez vrstvy, dropout, BN, residual/bottleneck, optimizer, LR, WD, batch, patience.

Výsledky (EUR)

- Najlepšie **Val RMSE ~54–55k**, **Test ~55k**.

Interpretácia

- Víťazia **Adam + LR ~1e-3**, dropout **0.05–0.10**, nízky WD.

Hyperparameter search (grid)

Čo som spravil

- Zúžil som grid okolo top nastavení z randomu.

Výsledky (EUR)

- Najlepšie **Val ~54.6k**, **Test ~54.6k**.

Interpretácia

- Nastavenie stabilné; ďalší progres potrebuje bohatšie vstupy.

EXPERIMENT 2

Data preprocessing and normalization

In [57]:
```
TARGET = "median_house_value"

EXCLUDE_E2 = {TARGET, "is_censored"}
if "region_id" in df.columns:
    EXCLUDE_E2.add("region_id")

CANDIDATES_E2 = (
    df.drop(columns=[c for c in EXCLUDE_E2 if c in df.columns], errors="ignore")
      .select_dtypes(include=[np.number]).columns.tolist()
)
```

In [58]:
```
print("EXP2 kandidáti:", CANDIDATES_E2)
```

```
EXP2 kandidáti: ['median_income', 'housing_median_age', 'total_rooms', 'total_bedroo
ms', 'population', 'households', 'latitude', 'longitude']
```

In [59]:
```
def select_top_raw_by_corr(frame: pd.DataFrame, target_col: str, k: int = 4) -> lis
    corr = frame[CANDIDATES_E2 + [target_col]].corr(numeric_only=True)[target_col]
    return corr.drop(target_col).abs().sort_values(ascending=False).head(k).index.t
```

In [60]:
```
def suggest_log_cols_for(frame: pd.DataFrame, cols: list[str], skew_threshold: floa
    s = frame[cols].skew(numeric_only=True)
    return s[s.abs() >= skew_threshold].index.tolist()
```

In [61]:
```
def make_preprocess(feature_cols: list[str], log_cols: list[str] | None = None):
    log_cols = [] if log_cols is None else list(log_cols)
    other    = [c for c in feature_cols if c not in log_cols]
    col_tf = ColumnTransformer(
        transformers=[
            ("log",  FunctionTransformer(np.log1p, validate=False), log_cols),
            ("num",  "passthrough", other),
        ],
        remainder="drop",
```

```
    )
    return Pipeline([("cols", col_tf), ("scaler", StandardScaler())])
```

Čo som spravil

- Z 8 kandidátov som vybral **Top-4 podľa |corr| s cieľom** na TRAINE.
- `log1p` len pre stĺpce s **|skew| ≥ 1** (určené na TRAINE), potom `StandardScaler`.

Výsledky

- Typické Top-4: `median_income`, `latitude`, `total_rooms`, `housing_median_age`.

Interpretácia

- Menšia dimenzia zrýchľuje tréning, ale znižuje maximálnu presnosť.

Data split

In [62]:
```
SEED = 42
TEST_FRAC = 0.10
VAL_FRAC  = 0.10

X_all = df[CANDIDATES_E2].copy()
y_all = df[TARGET].to_numpy()

bins_all = pd.qcut(y_all, q=10, labels=False, duplicates="drop")
```

In [63]:
```
X_trval, X_test2, y_trval, y_test2, bins_trval, bins_test = train_test_split(
    X_all, y_all, bins_all, test_size=TEST_FRAC, random_state=SEED, stratify=bins_a
)

val_rel = VAL_FRAC / (1.0 - TEST_FRAC)
bins_trval_local = pd.qcut(y_trval, q=10, labels=False, duplicates="drop")
X_train2, X_val2, y_train2, y_val2 = train_test_split(
    X_trval, y_trval, test_size=val_rel, random_state=SEED, stratify=bins_trval_loc
)
```

In [64]:
```
print(f"EXP2 shapes | train: {X_train2.shape}  val: {X_val2.shape}  test: {X_test2.
```

```
EXP2 shapes | train: (16512, 8)  val: (2064, 8)  test: (2064, 8)
```

In [65]:
```
y_train2_ser = pd.Series(y_train2, index=X_train2.index, name=TARGET)

corr_tbl = (
    pd.concat([X_train2[CANDIDATES_E2], y_train2_ser], axis=1)
      .corr(numeric_only=True)[TARGET]
      .drop(TARGET)
      .reindex(CANDIDATES_E2)
)
```

In [66]:
```
print("EXP2 |corr| (TRAIN) – top 8:")
display(corr_tbl.abs().sort_values(ascending=False).to_frame("abs_corr").head(8))
```

```
EXP2 |corr| (TRAIN) - top 8:
```

	abs_corr
median_income	0.692729
latitude	0.146938
total_rooms	0.136981
housing_median_age	0.103472
households	0.064002
total_bedrooms	0.049039
longitude	0.044149
population	0.025028

In [67]:
```
TOP4_E2 = corr_tbl.abs().sort_values(ascending=False).head(4).index.tolist()
print("EXP2 Top-4 (TRAIN |corr|):", TOP4_E2)
```

```
EXP2 Top-4 (TRAIN |corr|): ['median_income', 'latitude', 'total_rooms', 'housing_med
ian_age']
```

In [68]:
```
LOG_E2 = X_train2[TOP4_E2].skew(numeric_only=True).abs().pipe(lambda s: s[s >= 1.0]
print("EXP2 log_cols (TRAIN):", LOG_E2)
```

```
EXP2 log_cols (TRAIN): ['median_income', 'total_rooms']
```

Čo som spravil

- Použil som rovnakú kvantilovú stratifikáciu.

Výsledky

- Po preprocese: **Train (16.5k, 4)**, **Val (2.1k, 4)**, **Test (2.1k, 4)**.

Interpretácia

- Čisté porovnanie proti E1, zmena je len v počte vstupov.

Configuration

In [69]:
```
CONFIG_E2 = {
    "seed": SEED,
    "target": TARGET,
    "features": TOP4_E2,
    "preprocess": {
        "scaler": "standard",
        "log_cols": LOG_E2,
    },
    "feature_set": "exp2_top4",
}
```

In [70]:
```
preprocess_e2 = make_preprocess(CONFIG_E2["features"], CONFIG_E2["preprocess"]["log
Xtr_e2 = preprocess_e2.fit_transform(X_train2)
Xva_e2 = preprocess_e2.transform(X_val2)
Xte_e2 = preprocess_e2.transform(X_test2)

print("EXP2 n_features:", Xtr_e2.shape[1])
```

```
EXP2 n_features: 4
```

Čo som spravil

- Nastavil som `features = TOP4`, `log_cols` zo skew na TRAINE, `scaler="standard"`.

Výsledky

- Prehľadné a opakovateľné nastavenie.

Interpretácia

- Umožňuje zmerať kompromis „menej features vs. výkon".

Experiment tracking

In [71]:
```
baseline_e2 = DummyRegressor(strategy="median").fit(Xtr_e2, y_train2)

def _m(y_t, y_p):
    return {"rmse": float(np.sqrt(mean_squared_error(y_t, y_p))),
            "mae":  float(mean_absolute_error(y_t, y_p)),
            "r2":   float(r2_score(y_t, y_p))}

m_tr_e2 = _m(y_train2, baseline_e2.predict(Xtr_e2))
m_va_e2 = _m(y_val2,   baseline_e2.predict(Xva_e2))
m_te_e2 = _m(y_test2,  baseline_e2.predict(Xte_e2))
```

In [72]:
```
display(pd.DataFrame({"train": m_tr_e2, "val": m_va_e2, "test": m_te_e2}).round(2))
```

	train	val	test
rmse	118580.33	118956.83	117848.78
mae	88360.02	88658.38	88002.81
r2	-0.06	-0.06	-0.05

Čo som spravil

- Spustil som dummy medián ako referenčný model.

Výsledky (EUR)

- **RMSE ~118–119k**, **MAE ~88k**.

Interpretácia

- Slúži len ako spodná hranica.

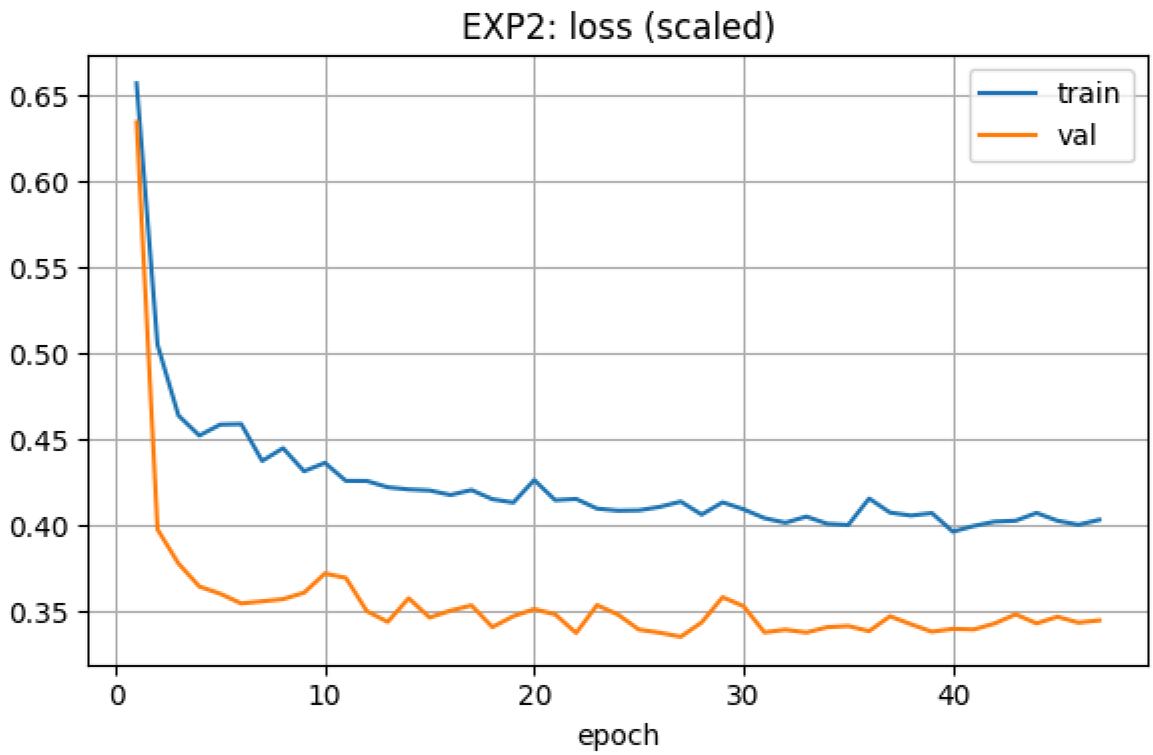
Experiments

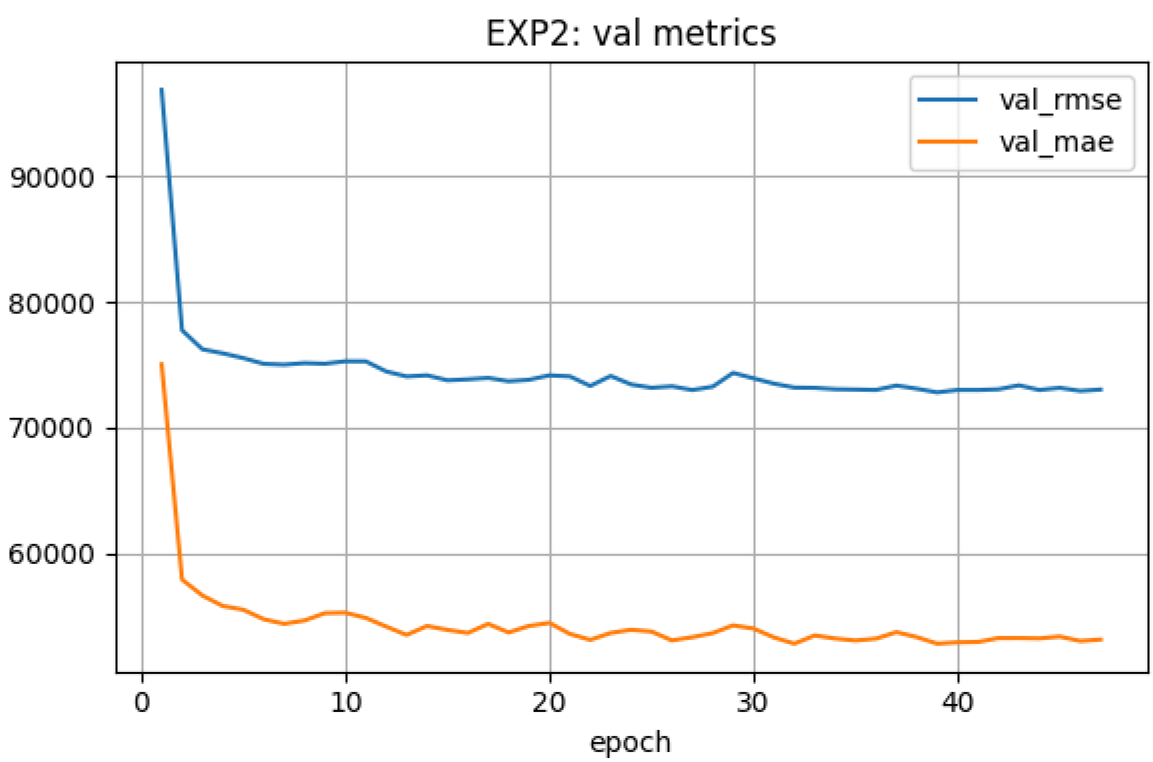
In [73]:
```
y_scaler = StandardScaler().fit(y_train2.reshape(-1,1))
y_train2_s = y_scaler.transform(y_train2.reshape(-1,1)).ravel()
y_val2_s   = y_scaler.transform(y_val2.reshape(-1,1)).ravel()
y_test2_s  = y_scaler.transform(y_test2.reshape(-1,1)).ravel()

CFG_E2 = DEFAULT_CFG | {"feature_set": CONFIG_E2["feature_set"]}

WANDB_GROUP = "EXP2-baseline"

tags = [CFG_E2["feature_set"], "baseline", "EXP2_top4"]
model_e2, hist_e2, res_e2 = run_experiment(
    CFG_E2, Xtr_e2, y_train2_s, Xva_e2, y_val2_s, Xte_e2, y_test2_s,
    wandb_tags=tags, run_name="EXPERIMENT2-baseline"
)
```

In [74]:
```
display(pd.DataFrame(res_e2).round(2))
```

	train	val	test
rmse	71332.88	72996.13	75179.42
mae	52076.80	53342.20	54484.72
r2	0.62	0.60	0.57

In [75]:
```
hd = pd.DataFrame(hist_e2)
plt.figure(figsize=(6,4))
plt.plot(hd["epoch"], hd["train_loss_s"], label="train"); plt.plot(hd["epoch"], hd[
plt.title("EXP2: loss (scaled)"); plt.xlabel("epoch"); plt.grid(True); plt.legend()

plt.figure(figsize=(6,4))
plt.plot(hd["epoch"], hd["val_rmse"], label="val_rmse"); plt.plot(hd["epoch"], hd["
plt.title("EXP2: val metrics"); plt.xlabel("epoch"); plt.grid(True); plt.legend();
```





Čo som spravil

- Trénoval som MLP ako v E1, ale so 4 vstupmi.

Výsledky (EUR)

- Train **~71k**, Val **~73k / ~53k MAE / R^2 ~0.60**, Test **~75k / ~55k MAE / R^2 ~0.57**.

Interpretácia

- Jasný pokles presnosti (menej informácií), bez výrazného overfitu.

Hyperparameter search (grid/random)

In [76]:
```
search_space = {
    "hidden_layers": [[256,128,64],[128,64,32],[256,128,64,32]],
    "dropout":       [0.00, 0.05, 0.10, 0.20, 0.30],
    "batchnorm":     [True, False],
    "residual":      [False, True],
    "bottleneck":    [False, True],
    "optimizer":     ["adam","rmsprop","sgd"],
    "lr":            [3e-4, 1e-3],
    "weight_decay": [0.0, 1e-5, 1e-4, 1e-3],
    "batch_size":    [512, 1024, 2048],
    "patience":      [10, 20, 30],
}
def _pick(k):
    return random.choice(search_space[k])

N_TRIALS = 16

WANDB_GROUP = "EXP2-random"
rows = []
```

In [77]:
```
for i in range(1, N_TRIALS+1):
    cfg = DEFAULT_CFG |{
        "hidden_layers": _pick("hidden_layers"),
        "dropout":      _pick("dropout"),
        "batchnorm":    _pick("batchnorm"),
        "residual":     _pick("residual"),
        "bottleneck":   _pick("bottleneck"),
        "optimizer":    _pick("optimizer"),
        "lr":           _pick("lr"),
        "weight_decay": _pick("weight_decay"),
        "batch_size":   _pick("batch_size"),
        "patience":     _pick("patience"),
        "seed":         random.randint(1, 10_000),
        "feature_set":  CONFIG_E2["feature_set"],
    }

    model_tmp, hist_tmp, res = run_experiment(
        cfg,
        Xtr_e2, y_train2_s,
        Xva_e2, y_val2_s,
        Xte_e2, y_test2_s,
        wandb_tags=[CONFIG_E2["feature_set"], "random", "EXP2_top4"],
        run_name=f"EXPERIMENT2-rand-{i:02d}"
    )

    rows.append({
        "i": i,
        "val_rmse": res["val"]["rmse"],
```

```
        "test_rmse": res["test"]["rmse"],
        "val_mae": res["val"]["mae"],
        "test_mae": res["test"]["mae"],
        "cfg": cfg
    })
```

In [78]:
```
df_rows = pd.DataFrame(rows)
display(df_rows.sort_values("test_rmse").head(10).round(3))
```

	i	val_rmse	test_rmse	val_mae	test_mae	cfg
12	13	71835.086	74327.703	51693.031	53171.566	{'seed': 9065, 'hidden_layers': [256, 128, 64,...
7	8	72054.359	74699.164	51976.797	53540.156	{'seed': 1313, 'hidden_layers': [256, 128, 64]...
10	11	72479.062	74782.102	52424.629	53674.266	{'seed': 3493, 'hidden_layers': [256, 128, 64,...
3	4	72665.438	74784.359	52597.496	53724.598	{'seed': 3007, 'hidden_layers': [256, 128, 64]...
5	6	72186.891	74867.141	52246.438	53532.004	{'seed': 6210, 'hidden_layers': [256, 128, 64]...
11	12	72363.711	74871.070	51527.621	53107.270	{'seed': 8901, 'hidden_layers': [256, 128, 64,...
14	15	72876.375	75064.609	52569.480	53867.004	{'seed': 7240, 'hidden_layers': [256, 128, 64,...
6	7	73293.875	75098.992	53534.516	54463.727	{'seed': 3567, 'hidden_layers': [256, 128, 64]...
2	3	72951.438	75746.203	53243.148	54508.277	{'seed': 1613, 'hidden_layers': [256, 128, 64]...
8	9	72767.305	75867.297	52201.207	54089.820	{'seed': 6869, 'hidden_layers': [256, 128, 64]...

In [79]:
```
grid = {
    "hidden_layers": [[256,128,64],[128,64,32]],
    "dropout": [0.00, 0.10],
    "optimizer": ["adam","rmsprop"],
    "lr": [3e-4, 1e-3],
    "weight_decay": [1e-4],
}

WANDB_GROUP = "EXP2-grid"

gkeys, gvals = list(grid.keys()), list(grid.values())
rows = []
idx = 1
```

In [80]:
```
for values in product(*gvals):
    cfg = DEFAULT_CFG | {k: v for k, v in zip(gkeys, values)} | {"feature_set": CON
```

```
    _, _, res = run_experiment(
        cfg,
        Xtr_e2, y_train2_s,
        Xva_e2, y_val2_s,
        Xte_e2, y_test2_s,
        wandb_tags=[CONFIG_E2["feature_set"], "grid", "EXP2_top4"],
        run_name=f"EXPERIMENT2-grid-{idx:02d}"
    )
    rows.append({"i": idx, "val_rmse": res["val"]["rmse"], "test_rmse": res["test"]
    idx += 1
```

In [81]:
```
pd.DataFrame(rows).sort_values("test_rmse").head(10).round(2)
```

Out[81]:

	i	val_rmse	test_rmse	cfg
3	4	71510.12	74957.34	{'seed': 46, 'hidden_layers': [256, 128, 64], ...
5	6	72466.07	75001.33	{'seed': 48, 'hidden_layers': [256, 128, 64], ...
6	7	72932.16	75167.34	{'seed': 49, 'hidden_layers': [256, 128, 64], ...
13	14	73295.26	75231.13	{'seed': 56, 'hidden_layers': [128, 64, 32], '...
15	16	73484.59	75568.80	{'seed': 58, 'hidden_layers': [128, 64, 32], '...
7	8	73273.70	75688.66	{'seed': 50, 'hidden_layers': [256, 128, 64], ...
4	5	73258.41	75735.23	{'seed': 47, 'hidden_layers': [256, 128, 64], ...
2	3	73179.38	75812.38	{'seed': 45, 'hidden_layers': [256, 128, 64], ...
9	10	73138.76	75979.05	{'seed': 52, 'hidden_layers': [128, 64, 32], '...
1	2	73023.39	76037.55	{'seed': 44, 'hidden_layers': [256, 128, 64], ...

Hyperparameter search (random)

Čo som spravil

- Spustil som 16 náhodných behov.

Výsledky (EUR)

- Najlepšie **Val ~71–72k**, **Test ~74–75k**.

Interpretácia

- Limit je v chudobnejšom featuringu, nie v nastaveniach.

Hyperparameter search (grid)

Čo som spravil

- Zúžil som grid okolo najlepších kombinácií.

Výsledky (EUR)

- Najlepšie **Val ~71.5k**, **Test ~75k**.

Interpretácia

- Potvrdzuje kompromis E2; na zlepšenie treba nové/features.

EXPERIMENT 3

Data preprocessing and normalization

In [82]:
```
TARGET = "median_house_value"
SEED = 42
K = 8

NUM_FEATURES = (
    df.drop(columns=[c for c in [TARGET, "is_censored", "region_id"] if c in df.col
      .select_dtypes(include=[np.number])
      .columns.tolist()
)
```

In [83]:
```
def suggest_log_cols(frame: pd.DataFrame, cols: list[str], skew_threshold: float =
    s = frame[cols].skew(numeric_only=True)
    return s[s.abs() >= skew_threshold].index.tolist()
```

In [84]:
```
def fit_geo_kmeans(Xtr_base: pd.DataFrame, n_clusters: int = K, seed: int = SEED):
    km = KMeans(n_clusters=n_clusters, random_state=seed, n_init=10)
    km.fit(Xtr_base[["latitude", "longitude"]].to_numpy())
    return km
```

In [85]:
```
def assign_regions(km, df_base: pd.DataFrame):
    rid = km.predict(df_base[["latitude", "longitude"]].to_numpy())
    reg = pd.get_dummies(pd.Series(rid, index=df_base.index), prefix="region", dtyp
    for i in range(K):
        c = f"region_{i}"
        if c not in reg.columns:
            reg[c] = 0
    reg = reg[[f"region_{i}" for i in range(K)]]
    out = pd.concat([df_base, reg], axis=1)
    assert len(out) == len(df_base) and out.index.equals(df_base.index)
    return out, rid
```

In [86]:
```
def compute_region_stats(rid_tr: np.ndarray, y_train: np.ndarray, index: pd.Index):
    y_tr_ser = pd.Series(y_train, index=index, name=TARGET)
    grp = pd.DataFrame({"region": rid_tr, TARGET: y_tr_ser.values}, index=index).gr
    r_mean  = grp[TARGET].mean()
    r_count = grp[TARGET].count()
    r_rankn = r_mean.rank(method="dense", ascending=True).astype(int)
    r_rankn = (r_rankn / r_rankn.max()).to_dict()
    return r_mean, r_count, r_rankn
```

In [87]:
```
def map_stats_to_df(df_out: pd.DataFrame, rid: np.ndarray, r_mean: pd.Series, r_cou
    df_out["region_mean"] = pd.Series(rid, index=df_out.index).map(r_mean).fillna(r
    df_out["region_size"] = pd.Series(rid, index=df_out.index).map(r_count).fillna(
    df_out["region_rank"] = pd.Series(rid, index=df_out.index).map(r_rankn).fillna(
```

In [88]:
```
def add_geo_interactions(*dfs):
    for d in dfs:
        if "median_income" in d.columns:
            d["income_lat"] = d["median_income"] * d["latitude"]
            d["income_lon"] = d["median_income"] * d["longitude"]
        d["lat2"] = d["latitude"] ** 2
        d["lon2"] = d["longitude"] ** 2
        d["lat_lon"] = d["latitude"] * d["longitude"]
```

In [89]:
```
def build_geo_blocks(Xtr_base: pd.DataFrame, Xva_base: pd.DataFrame, Xte_base: pd.D
    km = fit_geo_kmeans(Xtr_base)
    Xtr_r, rid_tr = assign_regions(km, Xtr_base)
    Xva_r, rid_va = assign_regions(km, Xva_base)
    Xte_r, rid_te = assign_regions(km, Xte_base)

    r_mean, r_count, r_rankn = compute_region_stats(rid_tr, y_train, Xtr_base.index

    map_stats_to_df(Xtr_r, rid_tr, r_mean, r_count, r_rankn)
    map_stats_to_df(Xva_r, rid_va, r_mean, r_count, r_rankn)
    map_stats_to_df(Xte_r, rid_te, r_mean, r_count, r_rankn)

    add_geo_interactions(Xtr_r, Xva_r, Xte_r)
    return Xtr_r, Xva_r, Xte_r
```

Čo som spravil

- Zobral som všetky numerické + pridal **geo-bloky**: KMeans(k≈8) na (lat,lon) → one-hot `region_*`.
- Z TRAINU som vypočítal regionálne štatistiky (`region_mean` , `region_size` , `region_rank`) a **interakcie** (`income_lat` , `income_lon` , `lat2` , `lon2` , `lat_lon`).
- `log1p` som aplikoval pre **nezáporné** stĺpce s **|skew| ≥ 1** (TRAINE) + `StandardScaler` .

Výsledky

- Po dedupe ~**24 vstupov**; preprocess fit len na TRAINE.

Interpretácia

- Geoinformácia výrazne pomáha — lepší signál o lokalite a hustote.

Data split

In [90]:
```
TEST_FRAC = 0.10
VAL_FRAC  = 0.10
```

```python
X_all = df[NUM_FEATURES].copy()
y_all = df[TARGET].to_numpy()

bins_all = pd.qcut(y_all, q=10, labels=False, duplicates="drop")

X_trval, X_test3, y_trval, y_test3, bins_trval, bins_test = train_test_split(
    X_all, y_all, bins_all, test_size=TEST_FRAC, random_state=SEED, stratify=bins_a
)
```

In [91]:
```python
val_rel = VAL_FRAC / (1.0 - TEST_FRAC)
bins_trval_local = pd.qcut(y_trval, q=10, labels=False, duplicates="drop")
X_train3, X_val3, y_train3, y_val3 = train_test_split(
    X_trval, y_trval, test_size=val_rel, random_state=SEED, stratify=bins_trval_loc
)
```

In [92]:
```python
print(f"EXP3 shapes | train: {X_train3.shape}  val: {X_val3.shape}  test: {X_test3.

X_train3_full, X_val3_full, X_test3_full = build_geo_blocks(X_train3, X_val3, X_tes
```

```
EXP3 shapes | train: (16512, 8)  val: (2064, 8)  test: (2064, 8)
```

In [93]:
```python
GEO_COLS = [c for c in X_train3_full.columns if c.startswith("region_")] + \
           [c for c in ["region_mean","region_size","region_rank",
                        "income_lat","income_lon","lat2","lon2","lat_lon"] if c in
FEATURES_E3 = [c for c in NUM_FEATURES if c in X_train3_full.columns] + GEO_COLS
```

In [94]:
```python
def suggest_log_cols_for(df_tr: pd.DataFrame, cand_cols, skew_threshold=1.0):
    s = df_tr[cand_cols].skew(numeric_only=True).abs()
    return s[s >= skew_threshold].index.tolist()

CAND_LOG = [c for c in FEATURES_E3 if c in X_train3_full.columns and X_train3_full[

LOG_E3 = suggest_log_cols_for(X_train3_full, CAND_LOG, skew_threshold=1.0)
```

In [95]:
```python
print("EXP3 n_features (pred dedupe):", len(FEATURES_E3))
print("EXP3 log_cols (TRAIN):", LOG_E3)
```

```
EXP3 n_features (pred dedupe): 27
EXP3 log_cols (TRAIN): ['median_income', 'total_rooms', 'total_bedrooms', 'populatio
n', 'households', 'region_0', 'region_1', 'region_3', 'region_4', 'region_5', 'regio
n_6', 'region_7', 'income_lat']
```

Čo som spravil

- Použil som rovnakú stratifikáciu; KMeans a mapovanie štatistík som **fitoval len na TRAINE**, aplikoval na VAL/TEST.

Výsledky

- Po preprocese: **Train (16.5k, ~24)**, **Val (2.1k, ~24)**, **Test (2.1k, ~24)**.

Interpretácia

- Minimalizovaný leakage

Configuration

In [96]:
```
seen=set(); FEATURES_E3_unique=[]
for c in FEATURES_E3:
    if c not in seen:
        FEATURES_E3_unique.append(c); seen.add(c)
LOG_E3 = [c for c in LOG_E3 if c in FEATURES_E3_unique]

CONFIG_E3 = {
    "seed": SEED,
    "target": TARGET,
    "features": FEATURES_E3_unique,
    "preprocess": {"scaler": "standard", "log_cols": LOG_E3},
    "feature_set": "exp3_allnum_geo",
}
print("EXP3 n_features (po dedupe):", len(CONFIG_E3["features"]))
```

```
EXP3 n_features (po dedupe): 24
```

In [97]:
```
def make_preprocess_e3(feature_cols: list[str], log_cols: list[str]):
    other_cols = [c for c in feature_cols if c not in log_cols]
    col_tf = ColumnTransformer(
        transformers=[
            ("log",  Pipeline([("imp", SimpleImputer(strategy="median")),
                               ("log", FunctionTransformer(np.log1p, validate=False
            ("num",  SimpleImputer(strategy="median"), other_cols),
        ],
        remainder="drop",
    )
    return Pipeline([
        ("cols", col_tf),
        ("scaler", StandardScaler()),
    ])
```

In [98]:
```
def make_preprocess_e3(feature_cols: list[str], log_cols: list[str]):
    other_cols = [c for c in feature_cols if c not in log_cols]
    col_tf = ColumnTransformer(
        transformers=[
            ("log",  Pipeline([("imp", SimpleImputer(strategy="median")),
                               ("log", FunctionTransformer(np.log1p, validate=False
            ("num",  SimpleImputer(strategy="median"), other_cols),
        ],
        remainder="drop",
    )
    return Pipeline([
        ("cols", col_tf),
        ("scaler", StandardScaler()),
    ])
```

In [99]:
```
preprocess_e3 = make_preprocess_e3(CONFIG_E3["features"], CONFIG_E3["preprocess"]["

Xtr_e3 = preprocess_e3.fit_transform(X_train3_full[CONFIG_E3["features"]])
Xva_e3 = preprocess_e3.transform(   X_val3_full[CONFIG_E3["features"]])
```

```
Xte_e3 = preprocess_e3.transform(   X_test3_full[CONFIG_E3["features"]])
print("EXP3 shapes po preprocese:", Xtr_e3.shape, Xva_e3.shape, Xte_e3.shape)
```

```
EXP3 shapes po preprocese: (16512, 24) (2064, 24) (2064, 24)
```

In [100…

```
y_scaler3 = _SS().fit(y_train3.reshape(-1,1))
y_train3_s = y_scaler3.transform(y_train3.reshape(-1,1)).ravel()
y_val3_s   = y_scaler3.transform(y_val3.reshape(-1,1)).ravel()
y_test3_s  = y_scaler3.transform(y_test3.reshape(-1,1)).ravel()

y_scaler = y_scaler3

AMP_DTYPE = torch.float32
```

Čo som spravil

- Nastavil som `features = NUM + GEO + interakcie`, `log_cols` z TRAINE, `scaler="standard"`.

Výsledky

- Jednotné miesto na úpravu k, interakcií aj log stĺpcov.

Interpretácia

- Uľahčuje porovnanie s E1/E2 a ďalšie iterácie.

Experiments

In [101…

```
def check(name, X, y):
    print(f"{name}: X NaN={np.isnan(X).any()}  X Inf={np.isinf(X).any()}  "
          f"y NaN={np.isnan(y).any()}  y Inf={np.isinf(y).any()}  shape={(X.shape,
check("TRAIN", Xtr_e3, y_train3_s)
check("VAL  ", Xva_e3, y_val3_s)
check("TEST ", Xte_e3, y_test3_s)

assert Xtr_e3.shape[0] == len(y_train3_s) and Xva_e3.shape[0] == len(y_val3_s) and
```

```
TRAIN: X NaN=False  X Inf=False  y NaN=False  y Inf=False  shape=((16512, 24), 1651
2)
VAL  : X NaN=False  X Inf=False  y NaN=False  y Inf=False  shape=((2064, 24), 2064)
TEST : X NaN=False  X Inf=False  y NaN=False  y Inf=False  shape=((2064, 24), 2064)
```

In [102…

```
CFG_E3 = DEFAULT_CFG | {"feature_set": CONFIG_E3["feature_set"]}

WANDB_GROUP = "EXP3-baseline"

tags = [CFG_E3["feature_set"], "baseline", "EXP3_geo"]
```

In [103…

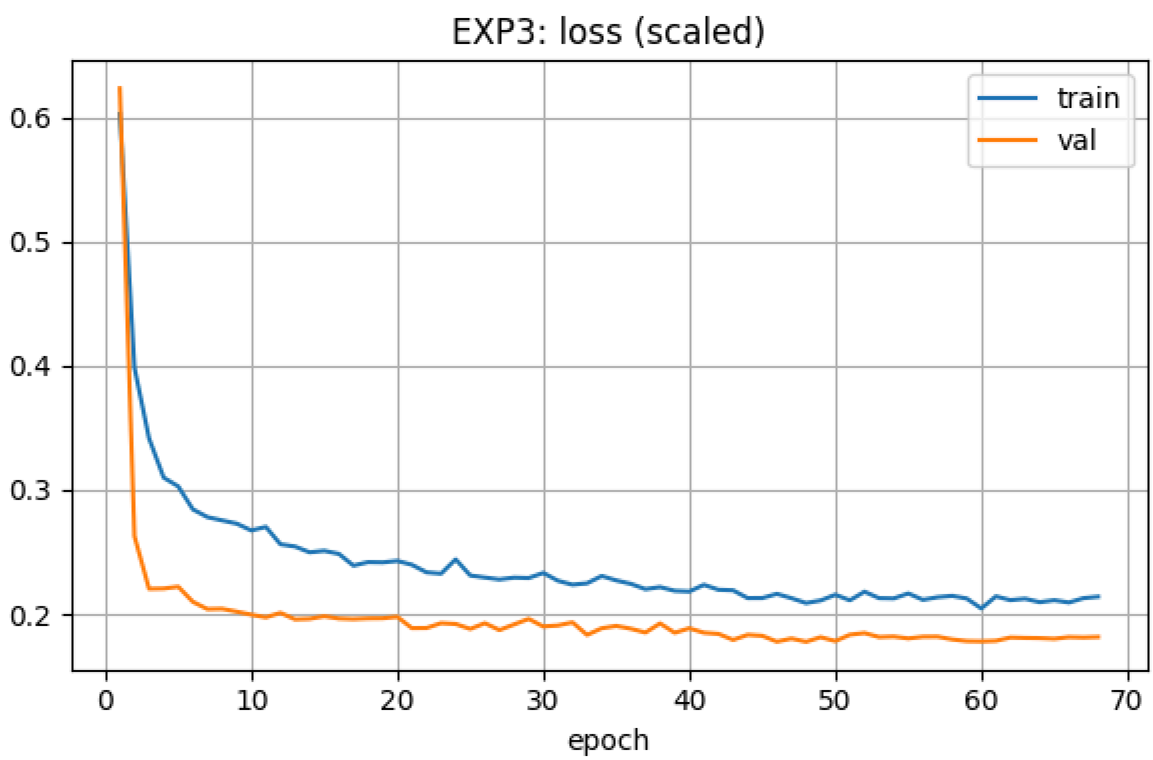
```
model_e3, hist_e3, res_e3 = run_experiment(
    CFG_E3,
    Xtr_e3, y_train3_s,
    Xva_e3, y_val3_s,
    Xte_e3, y_test3_s,
```

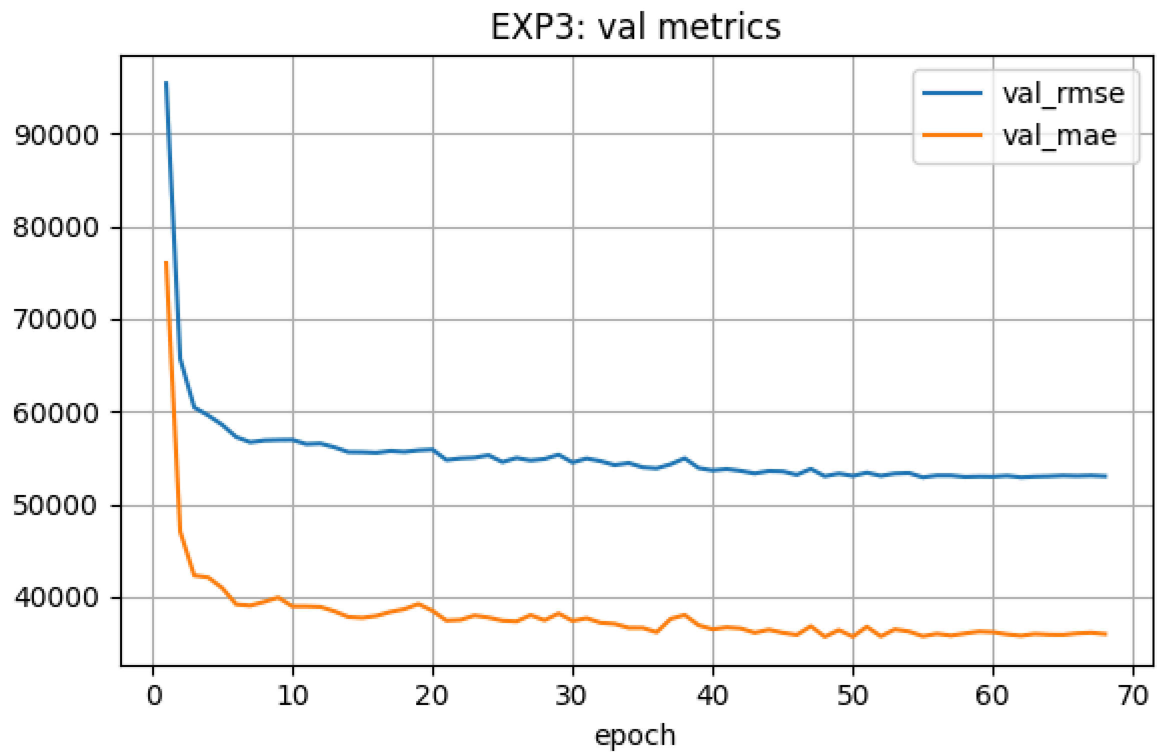
```
    wandb_tags=tags, run_name="EXPERIMENT3-baseline"
)

display(pd.DataFrame(res_e3).round(2))
```

	train	val	test
rmse	49696.92	53007.71	52879.08
mae	34034.26	35691.85	35599.61
r2	0.81	0.79	0.79

In [104…

```
hd = pd.DataFrame(hist_e3)
plt.figure(figsize=(6,4))
plt.plot(hd["epoch"], hd["train_loss_s"], label="train")
plt.plot(hd["epoch"], hd["val_loss_s"],   label="val")
plt.title("EXP3: loss (scaled)"); plt.xlabel("epoch"); plt.grid(True); plt.legend()

plt.figure(figsize=(6,4))
plt.plot(hd["epoch"], hd["val_rmse"], label="val_rmse")
plt.plot(hd["epoch"], hd["val_mae"],  label="val_mae")
plt.title("EXP3: val metrics"); plt.xlabel("epoch"); plt.grid(True); plt.legend();
```





Čo som spravil

- Trénoval som rovnaký MLP na rozšírených vstupoch.

Výsledky (EUR)

- Train **~49–50k**, Val **~52–53k / ~35–36k MAE / R^2 ~0.79**, Test **~52–53k / ~35–36k MAE / R^2 ~0.79**.

Interpretácia

- **Najlepší baseline**; Val ≈ Test → robustná generalizácia vďaka GEO.

Hyperparameter search (grid/random)

In [105…

```
assert Xtr_e3.shape[0] == len(y_train3_s)
assert Xva_e3.shape[0] == len(y_val3_s)
assert Xte_e3.shape[0] == len(y_test3_s)

y_scaler = y_scaler3
AMP_DTYPE = torch.float32

WANDB_GROUP = "EXP3-random"

N_TRIALS = 16
rows = []
```

In [106…

```
search_space = {
    "hidden_layers": [[256,128,64], [256,128,64,32], [128,64,32]],
```

```python
    "dropout":      [0.00, 0.05, 0.10, 0.15, 0.20],
    "batchnorm":    [True, False],
    "residual":     [False, True],
    "bottleneck":   [False, True],
    "optimizer":    ["adam","rmsprop","sgd"],
    "lr":           [3e-4, 1e-3],
    "weight_decay": [0.0, 1e-5, 1e-4],
    "batch_size":   [512, 1024, 2048],
    "patience":     [12, 16, 20],
}
def _pick(k):
    return random.choice(search_space[k])
```

In [107…

```python
for i in range(1, N_TRIALS+1):
    cfg = DEFAULT_CFG |{
        "hidden_layers": _pick("hidden_layers"),
        "dropout":      _pick("dropout"),
        "batchnorm":    _pick("batchnorm"),
        "residual":     _pick("residual"),
        "bottleneck":   _pick("bottleneck"),
        "optimizer":    _pick("optimizer"),
        "lr":           _pick("lr"),
        "weight_decay": _pick("weight_decay"),
        "batch_size":   _pick("batch_size"),
        "patience":     _pick("patience"),
        "seed":         random.randint(1, 100_000),
        "feature_set":  CONFIG_E3["feature_set"],
    }

    _, _, res = run_experiment(
        cfg,
        Xtr_e3, y_train3_s, Xva_e3, y_val3_s, Xte_e3, y_test3_s,
        wandb_tags=[CONFIG_E3["feature_set"], "random", "EXP3_geo"],
        run_name=f"EXPERIMENT3-random-{i:02d}"
    )

    rows.append({
        "i": i,
        "val_rmse":  res["val"]["rmse"],  "test_rmse":  res["test"]["rmse"],
        "val_mae":   res["val"]["mae"],   "test_mae":   res["test"]["mae"],
        "val_r2":    res["val"]["r2"],    "test_r2":    res["test"]["r2"],
        "cfg": cfg
    })
```

In [108…

```python
df_rand = pd.DataFrame(rows).sort_values("test_rmse").reset_index(drop=True)
display(df_rand[["i","val_rmse","test_rmse","val_mae","test_mae","val_r2","test_r2"
print("\nNajlepší random podľa test_rmse:\n", df_rand.iloc[0]["cfg"])
```

	i	val_rmse	test_rmse	val_mae	test_mae	val_r2	test_r2
0	1	52200.76	51982.09	34863.48	34637.98	0.80	0.79
1	3	53467.01	52931.83	36621.95	36207.17	0.79	0.79
2	12	52756.79	52942.74	34810.25	35117.98	0.79	0.79
3	4	53879.36	53301.43	37449.65	37087.46	0.78	0.78
4	14	54794.41	54836.19	36848.83	36923.93	0.78	0.77
5	5	55232.77	54856.29	37531.84	37490.34	0.77	0.77
6	9	55769.62	55084.78	38683.95	38356.59	0.77	0.77
7	15	55555.91	55158.04	38455.66	38433.46	0.77	0.77
8	6	55372.21	55357.55	37498.36	37780.49	0.77	0.77
9	2	55476.99	55426.52	37535.20	37309.23	0.77	0.77

```
Najlepší random podľa test_rmse:
 {'seed': 32707, 'hidden_layers': [256, 128, 64], 'batchnorm': True, 'dropout': 0.1
5, 'residual': False, 'bottleneck': True, 'optimizer': 'rmsprop', 'lr': 0.0003, 'wei
ght_decay': 1e-05, 'batch_size': 512, 'epochs': 200, 'patience': 20, 'grad_clip': 1.
0, 'feature_set': 'exp3_allnum_geo'}
```

In [109…

```
assert Xtr_e3.shape[0] == len(y_train3_s)
assert Xva_e3.shape[0] == len(y_val3_s)
assert Xte_e3.shape[0] == len(y_test3_s)

WANDB_GROUP = "EXP3-grid"
```

In [110…

```
candidate_grid = {
    "hidden_layers": [[256,128,64], [128,64,32]],
    "dropout":       [0.05, 0.10],
    "optimizer":     ["adam","rmsprop"],
    "lr":            [1e-3, 3e-4],
    "weight_decay":  [1e-5],
    "batch_size":    [1024],
    "patience":      [16],
}

gkeys = list(candidate_grid.keys())
gvals = list(candidate_grid.values())

rows = []
idx = 1
```

In [111…

```
for values in product(*gvals):
    cfg = DEFAULT_CFG | {k: v for k, v in zip(gkeys, values)} | {
        "feature_set": CONFIG_E3["feature_set"],
        "seed": 42 + idx,
    }

    _, _, res = run_experiment(
```

```
        cfg,
        Xtr_e3, y_train3_s, Xva_e3, y_val3_s, Xte_e3, y_test3_s,
        wandb_tags=[CONFIG_E3["feature_set"], "grid-24", "EXP3_geo"],
        run_name=f"EXPERIMENT3-grid-{idx:02d}"
    )

    rows.append({
        "i": idx,
        "val_rmse":  res["val"]["rmse"],
        "test_rmse": res["test"]["rmse"],
        "val_mae":   res["val"]["mae"],
        "test_mae":  res["test"]["mae"],
        "val_r2":    res["val"]["r2"],
        "test_r2":   res["test"]["r2"],
        "cfg": cfg
    })
    idx += 1
```

In [112…

```
df_grid24 = pd.DataFrame(rows).sort_values("test_rmse").reset_index(drop=True)
display(df_grid24[["i","val_rmse","test_rmse","val_mae","test_mae","val_r2","test_r
print("\nNajlepší grid podľa test_rmse:\n", df_grid24.iloc[0]["cfg"])
```

	i	val_rmse	test_rmse	val_mae	test_mae	val_r2	test_r2
0	1	49233.66	49306.96	31749.07	31401.44	0.82	0.82
1	3	50715.01	50760.66	33081.49	33030.86	0.81	0.80
2	5	51744.96	51395.43	34778.08	34327.30	0.80	0.80
3	4	52063.84	52132.87	34464.29	34116.51	0.80	0.79
4	7	51887.34	52412.87	34846.62	34927.98	0.80	0.79
5	11	52925.28	52535.75	35500.35	35339.98	0.79	0.79
6	8	53047.28	52831.57	35405.67	35539.93	0.79	0.79
7	13	53262.09	53074.62	36198.43	36407.70	0.79	0.79
8	2	53228.40	53156.32	35860.56	35745.72	0.79	0.79
9	15	53242.44	53259.51	35997.20	36169.20	0.79	0.78

```
Najlepší grid podľa test_rmse:
 {'seed': 43, 'hidden_layers': [256, 128, 64], 'batchnorm': True, 'dropout': 0.05,
'residual': False, 'bottleneck': True, 'optimizer': 'adam', 'lr': 0.001, 'weight_dec
ay': 1e-05, 'batch_size': 1024, 'epochs': 200, 'patience': 16, 'grad_clip': 1.0, 'fe
ature_set': 'exp3_allnum_geo'}
```

EXPERIMENT 3 — Hyperparameter search (random)

Čo som spravil

- Spustil som 16 náhodných behov na rozšírenom vstupe.

Výsledky (EUR)

- Najlepšie **Val ~52k**, **Test ~52k**.

Interpretácia

- Zisky citlivé najmä na dropout a LR; GEO prináša väčšinu prínosu.

EXPERIMENT 3 — Hyperparameter search (grid)

- Víťazných nastavena: vrstvy `[256,128,64]` / `[128,64,32]`, dropout **0.05–0.10**, **Adam**, **LR 1e-3**, **batch 1024**, **patience ~16**.

Výsledky (EUR)

- Najlepšie **Val ~49–50k**, **Test ~49–50k**.

Interpretácia

- Stabilné a opakovateľné; E3 je finálny model

In [ ]: