Student: Tyler James **Date:** 8-31-2025

This notebook covers:

1. **EDA** (data load, sanity checks, 6–8 visuals, brief insights)
2. **Cleaning & Feature Engineering** (missing/outliers checks, scaling choice, 1–2 engineered features)
3. **Custom k-NN** (Euclidean/Manhattan, uniform/distance; fit/predict/score`)
4. **Manual Calculations** (small, hand-worked distance + k-NN example)
5. **Evaluation & Tuning** (split, scaling comparison, 5-fold CV over k × metric × weights, plots)
6. **Compare to sklearn** + short note on **curse of dimensionality**

```
from pathlib import Path
import pandas as pd
from sklearn.datasets import fetch_california_housing

DATA_CSV = Path("california_housing.csv")

def load_california_df():
    if DATA_CSV.exists():
        return pd.read_csv(DATA_CSV)
    ds = fetch_california_housing(as_frame=True)
    df = ds.frame.rename(columns={"MedHouseValue": "MedHouseVal"})
    df.to_csv(DATA_CSV, index=False)
    return df

df = load_california_df()
print(df.shape, df.columns.tolist())
```

```
(20640, 9) ['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup', 'Latitude', 'Longitude', 'MedHouseVal']
```

Part 1: Data Loading and Exploration

1.1 Dataset loading and exploration

Dataset: California Housing Dataset (sklearn.datasets.fetch_california_housing)

Samples: 20,640 houses

Features: 8 features

- **MedInc**: Median income in block group
- **HouseAge**: Median house age in block group
- **AveRooms**: Average number of rooms per household
- **AveBedrms**: Average number of bedrooms per household

- **Population**: Block group population
- **AveOccup**: Average number of household members
- **Latitude**: Block group latitude
- **Longitude**: Block group longitude

Target: Median house value (in hundreds of thousands of dollars)

```
# Imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split, KFold
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score
from math import sqrt

# For parity check
from sklearn.neighbors import KNeighborsRegressor
```

```
# California Housing Dataset fetch
data = fetch_california_housing(as_frame=True)
df = data.frame.copy()
df.head()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	MedHouseVal
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25	3.413
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25	3.422

Next steps: Generate code with df New interactive sheet

```
df_clean = df.copy()
```

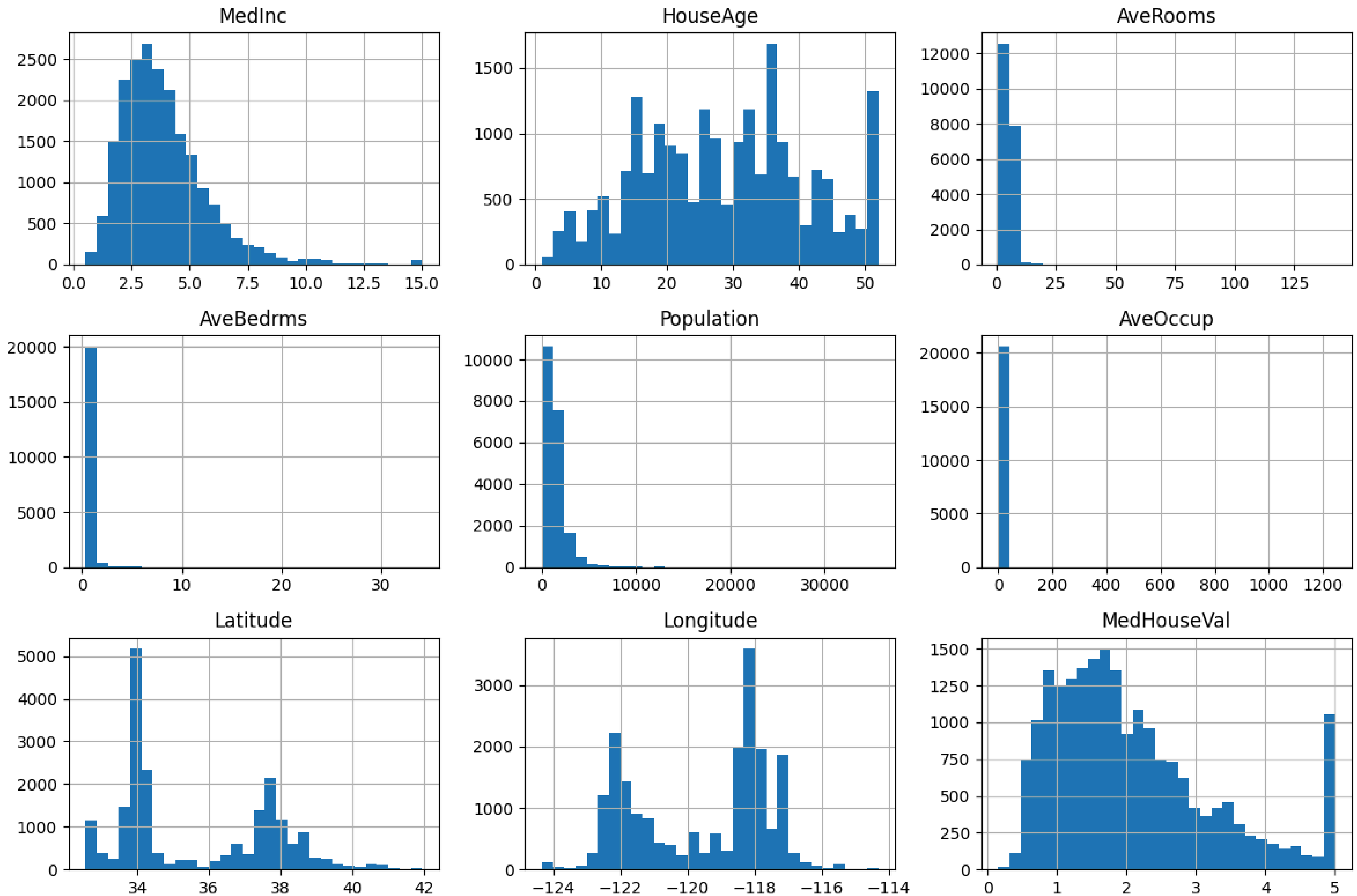
```
# Basic info & sanity checks
display(df.describe(include='all'))
print("Shape:", df.shape)
print("Missing values per column:\n", df.isna().sum())
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	MedHouseVal
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070655	35.631861	-119.569704	2.068558
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386050	2.135952	2.003532	1.153956
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692308	32.540000	-124.350000	0.149990
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429741	33.930000	-121.800000	1.196000
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818116	34.260000	-118.490000	1.797000
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282261	37.710000	-118.010000	2.647250
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333333	41.950000	-114.310000	5.000010

```
Shape: (20640, 9)
Missing values per column:
 MedInc         0
HouseAge       0
AveRooms       0
AveBedrms      0
Population     0
AveOccup       0
Latitude       0
Longitude      0
MedHouseVal    0
dtype: int64
```

```
# 6–8 quick visuals: histograms for all numeric columns
fig = plt.figure(figsize=(10, 6))
df_clean.hist(bins=30, figsize=(12,8))
plt.tight_layout(); plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```




```
# Identify Outliers (target)
q1, q3 = df_clean['MedHouseVal'].quantile([0.25, 0.75])
iqr = q3 - q1
lo, hi = q1 - 1.5*iqr, q3 + 1.5*iqr
mask = (df_clean['MedHouseVal'] < lo) | (df_clean['MedHouseVal'] > hi)
print(f"IQR fences: [{lo:.3f}, {hi:.3f}]  |  outliers: {mask.sum()} of {len(df_clean)} ({mask.mean()*100:.2f}%)")
```

```
IQR fences: [-0.981, 4.824]  |  outliers: 1071 of 20640 (5.19%)
```

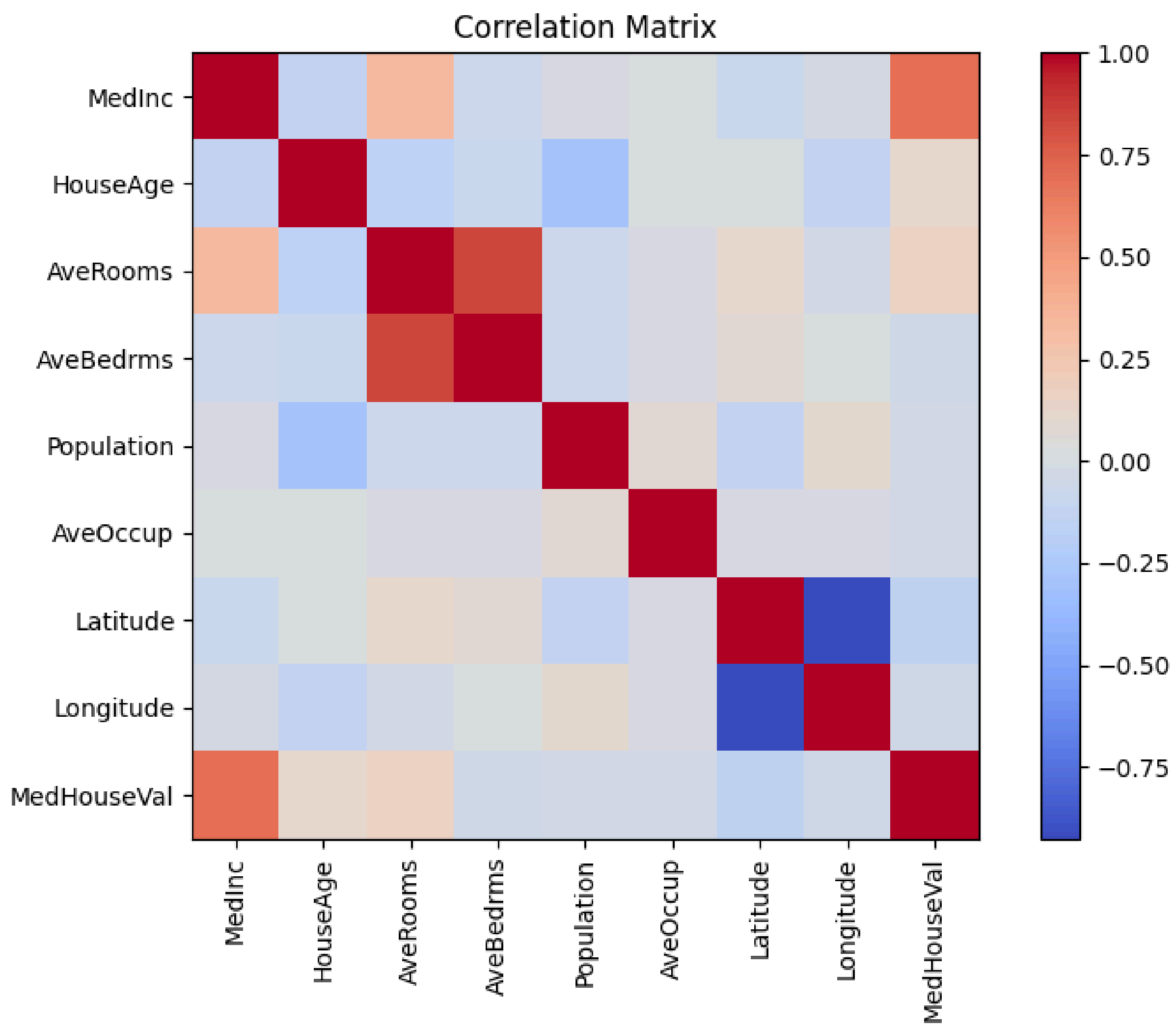
```
# Skewness check and transform suggestions
import numpy as np
```

```
num_cols = df_clean.select_dtypes(include=[np.number]).columns.tolist()
skews = df_clean[num_cols].skew(numeric_only=True).sort_values(ascending=False)
display(skews.to_frame("skew"))

high_right = skews[skews > 1.0].index.tolist()
mod_right  = skews[(skews > 0.5) & (skews <= 1.0)].index.tolist()
high_left  = skews[skews < -1.0].index.tolist()

print("Strong right-skew (consider log1p):", high_right)
print("Moderate right-skew (maybe √ or log1p):", mod_right)
print("Strong left-skew:", high_left)
```

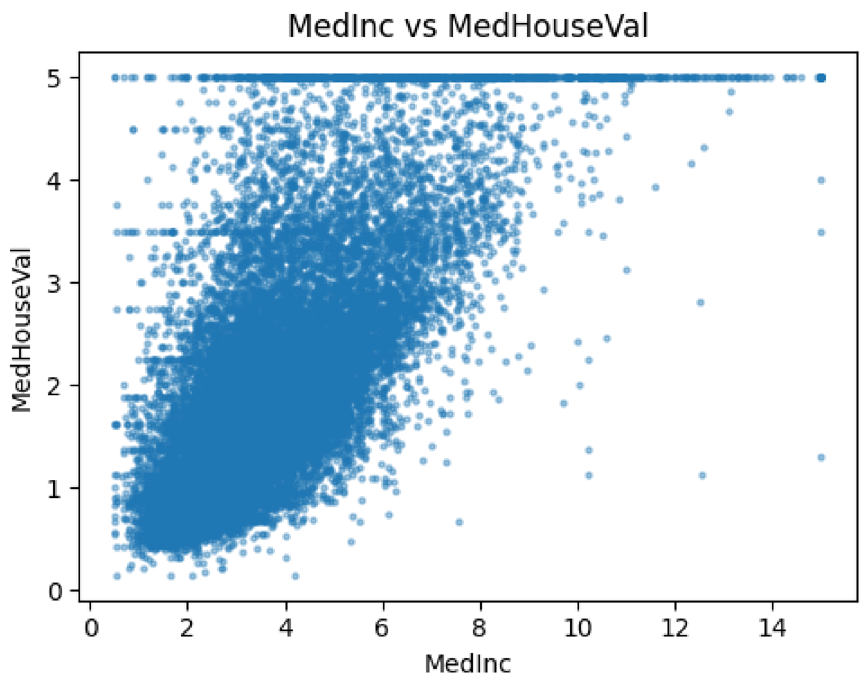
	skew
AveOccup	97.639561
AveBedrms	31.316956
AveRooms	20.697869
Population	4.935858
MedInc	1.646657
MedHouseVal	0.977763
Latitude	0.465953
HouseAge	0.060331
Longitude	-0.297801

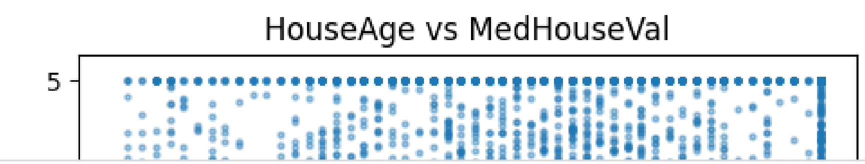
```
Strong right-skew (consider log1p): ['AveOccup', 'AveBedrms', 'AveRooms', 'Population', 'MedInc']
Moderate right-skew (maybe √ or log1p): ['MedHouseVal']
Strong left-skew: []
```

```
# Correlation heatmap
corr = df_clean.corr(numeric_only=True)
plt.figure(figsize=(8,6))
plt.imshow(corr, cmap='coolwarm', interpolation='nearest')
plt.colorbar()
plt.xticks(range(len(corr.columns)), corr.columns, rotation=90)
plt.yticks(range(len(corr.columns)), corr.columns)
plt.title("Correlation Matrix")
plt.tight_layout()
plt.show()
```

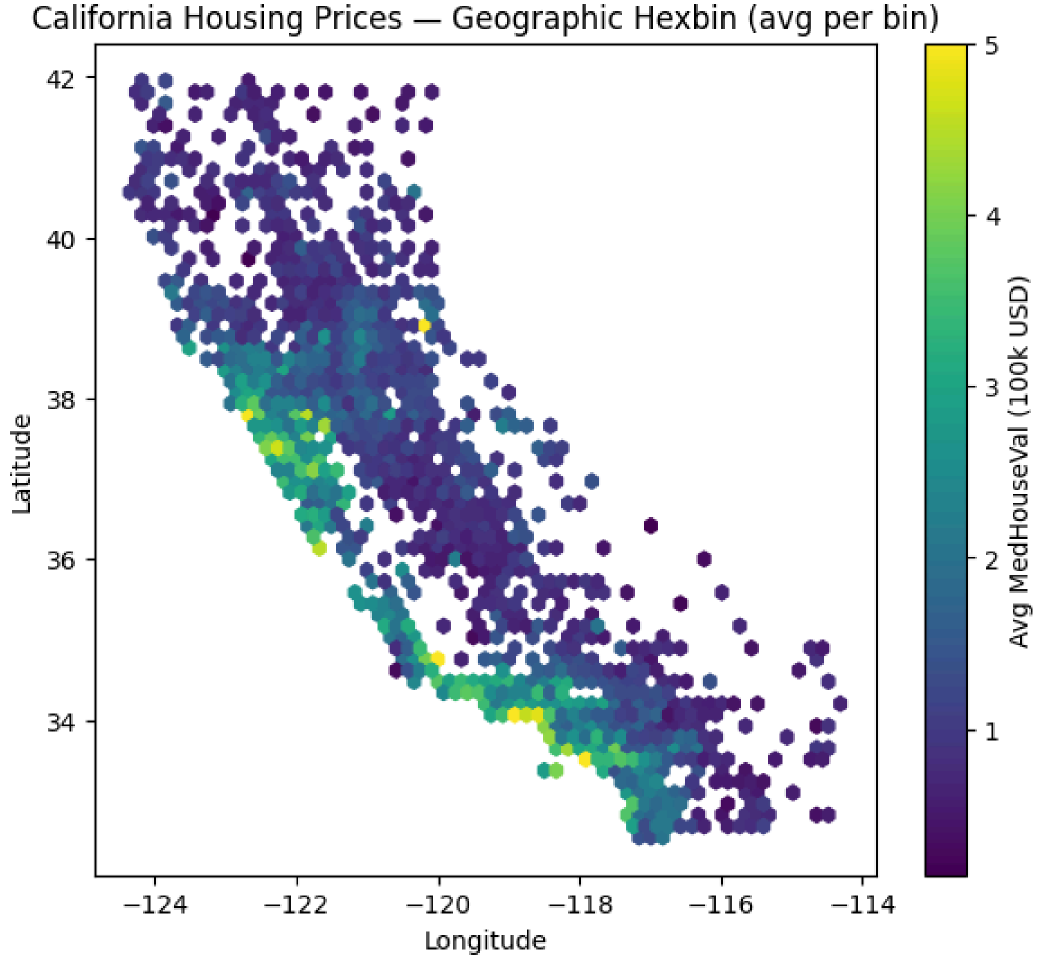



```
# Selected scatter plots vs target
features = [c for c in df_clean.columns if c != 'MedHouseVal']
for c in features[:4]:
    plt.figure(figsize=(5,4))
    plt.scatter(df_clean[c], df_clean['MedHouseVal'], s=5, alpha=0.4)
    plt.xlabel(c); plt.ylabel('MedHouseVal'); plt.title(f'{c} vs MedHouseVal')
    plt.tight_layout(); plt.show()
```






```
# Geography: visualize MedHouseVal across latitude/longitude
plt.figure(figsize=(7,6))
hb = plt.hexbin(df_clean['Longitude'], df_clean['Latitude'], C=df_clean['MedHouseVal'],
                gridsize=60, reduce_C_function=np.mean)
plt.colorbar(hb, label='Avg MedHouseVal (100k USD)')
plt.xlabel('Longitude'); plt.ylabel('Latitude')
plt.title('California Housing Prices — Geographic Hexbin (avg per bin)')
plt.show()

# Simple coastal vs inland flag using longitude (more negative ≈ coastal)
coastal = df_clean['Longitude'] < -122.0
print("Coastal share:", coastal.mean()*100, "%")
print("Avg price coastal:", df_clean.loc[coastal, 'MedHouseVal'].mean())
print("Avg price inland :", df_clean.loc[~coastal, 'MedHouseVal'].mean())

# Split by latitude (SoCal vs NorCal proxy) and compare means
south = df_clean['Latitude'] < 36.5
print("South share:", south.mean()*100, "%")
print("Avg price south:", df_clean.loc[south, 'MedHouseVal'].mean())
print("Avg price north:", df_clean.loc[~south, 'MedHouseVal'].mean())
```




```
Coastal share: 19.219961240310077 %
Avg price coastal: 2.442308817746408
Avg price inland : 1.9796318317039527
South share: 58.94379844961241 %
Avg price south: 2.1294053238533617
Avg price north: 1.981200783573283
```

```
# Engineered features (CLEAN)
df_clean['RoomsPerHousehold'] = df_clean['AveRooms'] / (df_clean['AveOccup'] + 1e-6)
df_clean['BedroomsPerRoom']   = df_clean['AveBedrms'] / (df_clean['AveRooms'] + 1e-6)
display(df_clean.head())
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	MedHouseVal	RoomsPerHousehold	BedroomsPerRoom
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526	2.732918	0.146591
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585	2.956683	0.155797
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521	2.957660	0.129516
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25	3.413	2.283153	0.184458
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25	3.422	2.879645	0.172096

```
# Outlier Table
import numpy as np, pandas as pd
from scipy import stats
```

```
def detect_outliers_iqr(df, col):
    q1, q3 = df[col].quantile([0.25, 0.75]); iqr = q3 - q1
    lo, hi = q1 - 1.5*iqr, q3 + 1.5*iqr
    return int(((df[col] < lo) | (df[col] > hi)).sum())

def detect_outliers_zscore(df, col, thr=3):
    z = np.abs(stats.zscore(df[col].dropna()))
    return int((z > thr).sum())

num_feats = [
    'MedInc','HouseAge','AveRooms','AveBedrms','Population','AveOccup',
    'Latitude','Longitude','RoomsPerHousehold','BedroomsPerRoom'
]

out_tbl = pd.DataFrame({
    'feature': num_feats,
    'iqr_outliers': [detect_outliers_iqr(df_clean, c) for c in num_feats],
    'zscore_outliers': [detect_outliers_zscore(df_clean, c) for c in num_feats],
})
display(out_tbl.sort_values('iqr_outliers', ascending=False).reset_index(drop=True))
```

	feature	iqr_outliers	zscore_outliers
0	AveBedrms	1424	145
1	Population	1196	342
2	AveOccup	711	8
3	MedInc	681	345
4	BedroomsPerRoom	591	284
5	AveRooms	511	133
6	RoomsPerHousehold	402	139
7	HouseAge	0	0
8	Longitude	0	0
9	Latitude	0	0

1.2 Exploratory Data Analysis (EDA)

The analysis of the California housing data shows a few key things. First, the price of a house is tied to the money people make in that area. The Median Income has the strongest link to house price. Average Rooms and House Age also matter, but income is the biggest factor. The plots confirm what nearly everyone knows about most areas: the most expensive houses are clustered along the coast, especially near cities like LA and San Francisco. This confirms that location is a huge part of home pricing.

There were a few problems to fix. Features like Population and Median Income, are very skewed, most values are low, but a few are much higher (outliers). Another issue is the datasets highest home price is $500,001. Because of this, the model won't be able to learn the actual value differences between more expensive homes, which will limit how accurate the final predictions are for expensive properties.

To fix the features, use Feature Scaling to balance everything, and use outlier handling to stop extreme values from ruining the k-NN distances.

Part 2 — Cleaning & *Feature Engineering*

2.1 / 2.3 Missing Value Analysis, Feature Engineering

```
# Missing values (California Housing typically has none)
print("Missing values per column:\n", df_clean.isna().sum())

# Engineered features on CLEAN data (correct)
df_clean['RoomsPerHousehold'] = df_clean['AveRooms'] / (df_clean['AveOccup'] + 1e-6)
df_clean['BedroomsPerRoom']   = df_clean['AveBedrms'] / (df_clean['AveRooms'] + 1e-6)

display(df_clean.head())
```

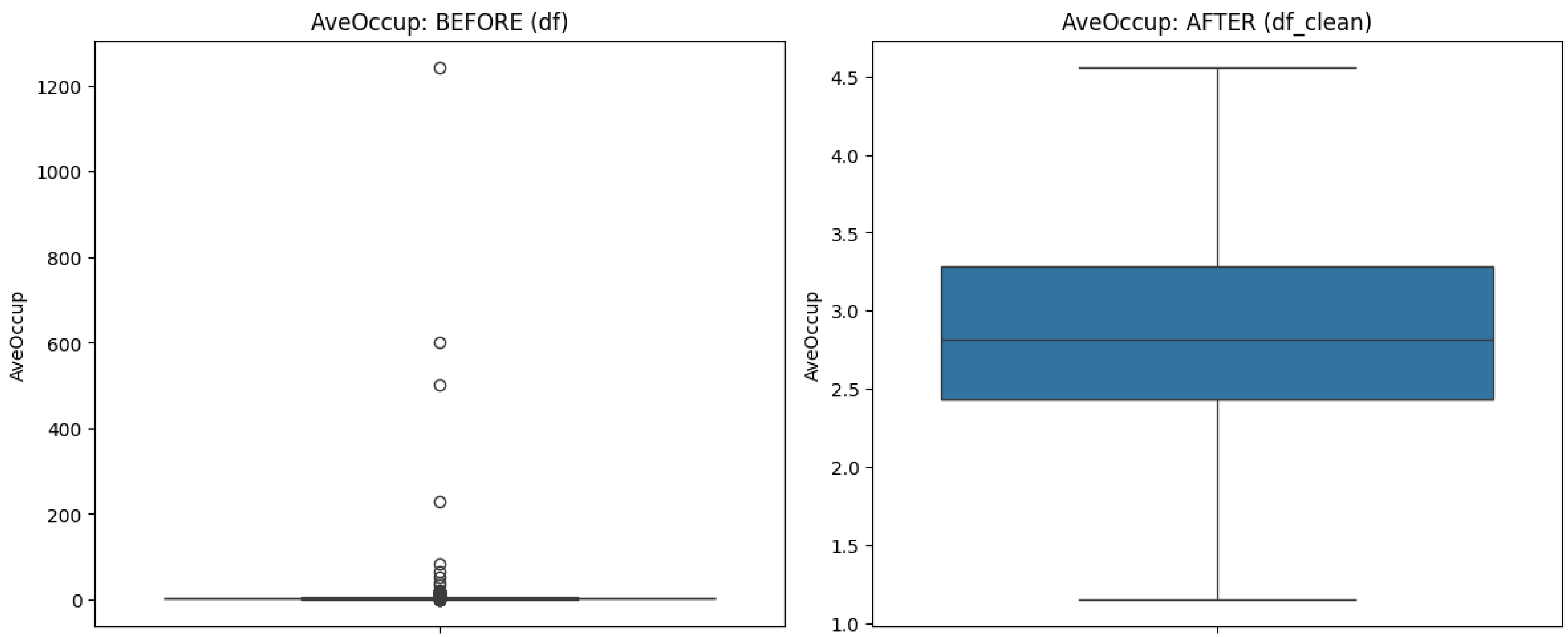
```
Missing values per column:
 MedInc               0
HouseAge             0
AveRooms             0
AveBedrms            0
Population           0
AveOccup             0
Latitude             0
Longitude            0
MedHouseVal          0
RoomsPerHousehold    0
BedroomsPerRoom      0
dtype: int64
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	MedHouseVal	RoomsPerHousehold	BedroomsPerRoom
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526	2.732918	0.146591
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585	2.956683	0.155797
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521	2.957660	0.129516
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25	3.413	2.283153	0.184458
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25	3.422	2.879645	0.172096

2.2 Outlier Detection and Handling

```
# --- Handling Choice: IQR Clipping on AveOccup (apply to CLEAN COPY) ---
Q1 = df_clean['AveOccup'].quantile(0.25)
Q3 = df_clean['AveOccup'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5*IQR
upper_bound = Q3 + 1.5*IQR

df_clean['AveOccup'] = df_clean['AveOccup'].clip(lower=lower_bound, upper=upper_bound)
```

```
# (optional visualization)
import matplotlib.pyplot as plt, seaborn as sns
plt.figure(figsize=(12,5))
plt.subplot(1,2,1); sns.boxplot(y=df['AveOccup']);        plt.title('AveOccup: BEFORE (df)')
plt.subplot(1,2,2); sns.boxplot(y=df_clean['AveOccup']);  plt.title('AveOccup: AFTER (df_clean)')
plt.tight_layout(); plt.show()
```



Removed Outliers

```
# Verify IQR clipping actually removed outliers on df_clean['AveOccup']
Q1, Q3 = df['AveOccup'].quantile([0.25, 0.75])          # bounds on RAW df (for reference)
IQR = Q3 - Q1
lo, hi = Q1 - 1.5*IQR, Q3 + 1.5*IQR

before = ((df['AveOccup'] < lo) | (df['AveOccup'] > hi)).sum()
after  = ((df_clean['AveOccup'] < lo) | (df_clean['AveOccup'] > hi)).sum()

print(f"AveOccup outliers BEFORE (raw df):  {before}")
print(f"AveOccup outliers AFTER  (df_clean): {after}")    # expect 0 after clipping
```

```
AveOccup outliers BEFORE (raw df):  711
AveOccup outliers AFTER  (df_clean): 0
```

Part 3: Custom k-NN Implementation

Supports:

- Distance metrics: **euclidean**, **manhattan**
- Weights: **uniform** (simple average), **distance** (1 / (d + ε))

```
knn = KNNRegressor(k=5, metric='euclidean', weights='uniform')
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
knn.score(X_test, y_test)  # R^2
```

```
# Code (Custom KNN class)
class KNNRegressor:
    def __init__(self, k=5, metric='euclidean', weights='uniform', eps=1e-9):
        assert metric in ('euclidean', 'manhattan')
        assert weights in ('uniform', 'distance')
        self.k = k
        self.metric = metric
        self.weights = weights
        self.eps = eps
        self._X = None
        self._y = None

    def fit(self, X, y):
        self._X = np.asarray(X, dtype=float)
        self._y = np.asarray(y, dtype=float).reshape(-1)
        return self

    def _pairwise_distances(self, X):
        X = np.asarray(X, dtype=float)
        if self.metric == 'euclidean':
            # (x - y)^2 = x^2 + y^2 - 2xy
            X2 = np.sum(X**2, axis=1, keepdims=True)
            Y2 = np.sum(self._X**2, axis=1)
            XY = X @ self._X.T
            d2 = X2 + Y2 - 2*XY
            np.maximum(d2, 0, out=d2)  # numerical safety
            return np.sqrt(d2)
        else:  # manhattan
            # Vectorized but memory-friendly loop
            d = np.empty((X.shape[0], self._X.shape[0]))
            for i in range(X.shape[0]):
                d[i] = np.sum(np.abs(self._X - X[i]), axis=1)
            return d

    def predict(self, X):
        D = self._pairwise_distances(X)  # (n_test, n_train)
        idx = np.argpartition(D, self.k, axis=1)[:, :self.k]
        rows = np.arange(D.shape[0])[:, None]
        d_k = D[rows, idx]
        y_k = self._y[idx]
```

```
        if self.weights == 'uniform':
            return np.mean(y_k, axis=1)
        else:
            w = 1.0 / (d_k + self.eps)
            w_sum = np.sum(w, axis=1, keepdims=True)
            return np.sum(w * y_k, axis=1) / w_sum[:,0]

    def score(self, X, y_true):
        y_pred = self.predict(X)
        return r2_score(y_true, y_pred)
```

Part 4: Manual Calculations (Proof of Understanding)

Part 5: Model Evaluation and Hyperparameter Tuning

```
# Train/test split and target
from sklearn.model_selection import train_test_split, KFold
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from math import sqrt
import pandas as pd

X = df_clean.drop(columns=['MedHouseVal']).values
y = df_clean['MedHouseVal'].values

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

scalers = {
    'standard': StandardScaler(),
    'minmax': MinMaxScaler()
}
k_values = [3,5,7,9,11,15,21]
metrics = ['euclidean', 'manhattan']
weights_list = ['uniform', 'distance']

cv = KFold(n_splits=5, shuffle=True, random_state=42)
results = []

for sc_name, scaler in scalers.items():
    X_tr = scaler.fit_transform(X_train)
    X_te = scaler.transform(X_test)

    for metric in metrics:
        for weights in weights_list:
            for k in k_values:
                fold_scores = []
                for tr_idx, va_idx in cv.split(X_tr):
                    X_tr_fold, X_va_fold = X_tr[tr_idx], X_tr[va_idx]
                    y_tr_fold, y_va_fold = y_train[tr_idx], y_train[va_idx]
```

```
                knn = KNNRegressor(k=k, metric=metric, weights=weights)
                knn.fit(X_tr_fold, y_tr_fold)
                fold_scores.append(knn.score(X_va_fold, y_va_fold))

            mean_cv = np.mean(fold_scores)
            knn.fit(X_tr, y_train)
            test_r2 = knn.score(X_te, y_test)

            results.append({
                'scaler': sc_name, 'metric': metric, 'weights': weights,
                'k': k, 'cv_r2': mean_cv, 'test_r2': test_r2
            })

res_df = pd.DataFrame(results).sort_values('cv_r2', ascending=False)
display(res_df.head(10))

best = res_df.iloc[0]
print("\nBest Config:\n", best)
```

	scaler	metric	weights	k	cv_r2	test_r2
53	minmax	manhattan	distance	11	0.777664	0.776551
54	minmax	manhattan	distance	15	0.776796	0.775096
52	minmax	manhattan	distance	9	0.775924	0.775236
55	minmax	manhattan	distance	21	0.775348	0.772214
46	minmax	manhattan	uniform	11	0.773642	0.772529
51	minmax	manhattan	distance	7	0.772355	0.776052
45	minmax	manhattan	uniform	9	0.772041	0.771362
47	minmax	manhattan	uniform	15	0.771847	0.769854
48	minmax	manhattan	uniform	21	0.769658	0.766316
44	minmax	manhattan	uniform	7	0.768919	0.773607

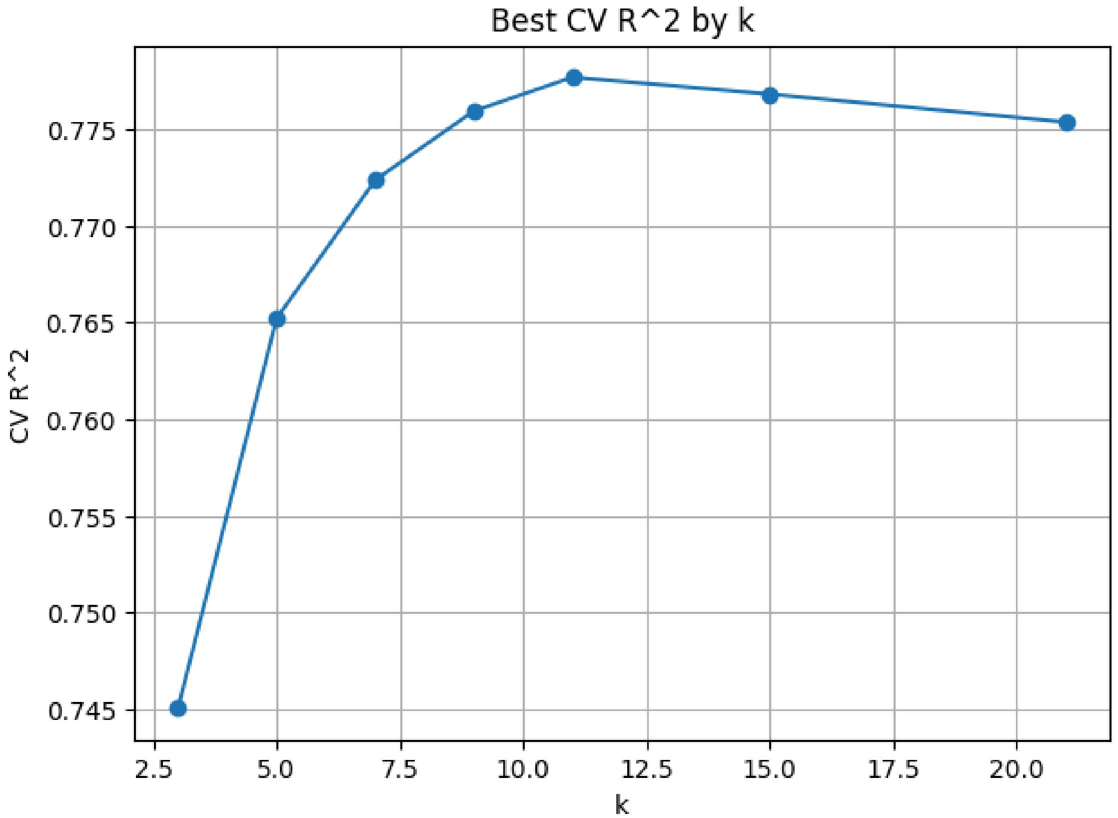
```
Best Config:
 scaler        minmax
metric     manhattan
weights     distance
k                 11
cv_r2       0.777664
test_r2     0.776551
Name: 53, dtype: object
```

```
# --- Sklearn parity check (uses the selected scaler) ---
from math import sqrt
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.neighbors import KNeighborsRegressor

best_scaler = scalers[best['scaler']]
X_tr_best = best_scaler.fit_transform(X_train)
X_te_best = best_scaler.transform(X_test)
```

```
sk_knn = KNeighborsRegressor(
    n_neighbors=int(best['k']),
    metric=best['metric'],
    weights=best['weights']
)
sk_knn.fit(X_tr_best, y_train)
sk_pred = sk_knn.predict(X_te_best)

print(
    f"Sklearn KNN — RMSE: {sqrt(mean_squared_error(y_test, sk_pred)):.4f} "
    f"| R^2: {r2_score(y_test, sk_pred):.4f}"
)
```

```
Sklearn KNN — RMSE: 0.5411 | R^2: 0.7766
```

```
# Quick plot: best CV score for each k
best_by_k = (res_df.sort_values('cv_r2', ascending=False)
                  .groupby('k', as_index=False).first()
                  .sort_values('k'))
plt.figure(figsize=(7,5))
plt.plot(best_by_k['k'], best_by_k['cv_r2'], marker='o')
plt.xlabel('k'); plt.ylabel('CV R^2'); plt.title('Best CV R^2 by k')
plt.grid(True)
plt.show()

best_by_k
```



	k	scaler	metric	weights	cv_r2	test_r2
0	3	minmax	manhattan	distance	0.745076	0.748741
1	5	minmax	manhattan	distance	0.765218	0.769557
2	7	minmax	manhattan	distance	0.772355	0.776052
3	9	minmax	manhattan	distance	0.775924	0.775236
4	11	minmax	manhattan	distance	0.777664	0.776551
5	15	minmax	manhattan	distance	0.776796	0.775096
6	21	minmax	manhattan	distance	0.775348	0.772214

Next steps: Generate code with best_by_k New interactive sheet

```
# Final fit with the single chosen configuration (auto-pick = row 0 of res_df)
best = res_df.iloc[0]
scaler = scalers[best['scaler']]
X_tr = scaler.fit_transform(X_train)
X_te = scaler.transform(X_test)

final_knn = KNNRegressor(k=int(best['k']), metric=best['metric'], weights=best['weights'])
final_knn.fit(X_tr, y_train)
y_pred = final_knn.predict(X_te)

rmse = sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)
print("Chosen:", dict(best))
```

```
Chosen: {'scaler': 'minmax', 'metric': 'manhattan', 'weights': 'distance', 'k': np.int64(11), 'cv_r2': np.float64(0.7776644551751888), 'test_r2': np.float64(0.7765509678952219)}
Test RMSE: 0.5411, Test R^2: 0.7766
```