Importing dataset and libraries

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import fetch_california_housing

# Load dataset
housing = fetch_california_housing(as_frame=True)
df = housing.frame
df.head()
```

Out[1]:

	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

EDA on dataset

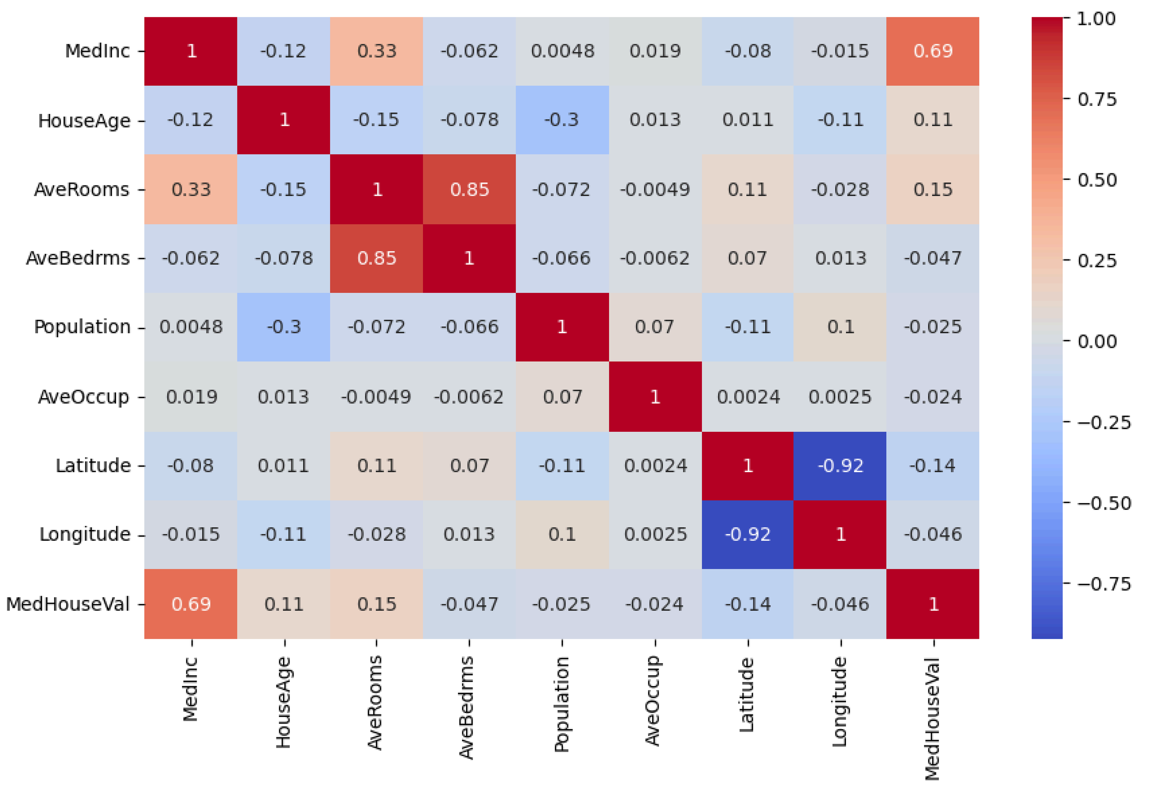
In [2]:
```python
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   MedInc       20640 non-null  float64
 1   HouseAge     20640 non-null  float64
 2   AveRooms     20640 non-null  float64
 3   AveBedrms    20640 non-null  float64
 4   Population   20640 non-null  float64
 5   AveOccup     20640 non-null  float64
 6   Latitude     20640 non-null  float64
 7   Longitude    20640 non-null  float64
 8   MedHouseVal  20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
```

Out[2]:

	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

In [3]:
```python
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.show()
```



Data Pre-processing

There doesn't seem to be any null values that need to be imputed

In [4]:
```python
df.isnull().sum()
```

Out[4]:
```
MedInc         0
HouseAge       0
AveRooms       0
AveBedrms      0
Population     0
AveOccup       0
Latitude       0
Longitude      0
MedHouseVal    0
dtype: int64
```

In [5]:
```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
features = df.drop('MedHouseVal', axis=1)
scaled_features = scaler.fit_transform(features)

X = pd.DataFrame(scaled_features, columns=features.columns)
y = df['MedHouseVal']
```

Train-Test split

In [6]:
```python
from sklearn.model_selection import train_test_split

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

Model Training and saving

In [7]:
```python
import os
import joblib

from sklearn.linear_model import LinearRegression, Ridge
from sklearn.tree import DecisionTreeRegressor
from sklearn.neural_network import MLPRegressor
from xgboost import XGBRegressor

# creating models directory
model_dir = "models"
os.makedirs(model_dir, exist_ok=True)
```

In [8]:
```python
models = {
    "LinearRegression": LinearRegression(),
    "DecisionTree": DecisionTreeRegressor(random_state=42),
    "NeuralNetwork": MLPRegressor(hidden_layer_sizes=(64, 32), max_iter=1000, random_state=42),
    "XGBoost": XGBRegressor(n_estimators=100, random_state=42),
    "Ridge": Ridge(alpha=1.0)
}

# Fitting each model
for name, model in models.items():
    print(f"Training {name}...")
    model.fit(X_train, y_train)
    # Saving the model to disk
    joblib.dump(model, os.path.join(model_dir, f"{name}.pkl"))
    print(f"{name} model saved as {name}.pkl\n")
```

```
Training LinearRegression...
LinearRegression model saved as LinearRegression.pkl

Training DecisionTree...
DecisionTree model saved as DecisionTree.pkl

Training NeuralNetwork...
NeuralNetwork model saved as NeuralNetwork.pkl

Training XGBoost...
XGBoost model saved as XGBoost.pkl

Training Ridge...
Ridge model saved as Ridge.pkl
```

In [9]:
```python
import json
import numpy as np
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# Dictionary to hold evaluation metrics
evaluation_results = {}

def evaluate_model(name, model, X_test, y_test):
    preds = model.predict(X_test)
    rmse = float(np.sqrt(mean_squared_error(y_test, preds)))
    mae = float(mean_absolute_error(y_test, preds))
    r2 = float(r2_score(y_test, preds))

    # Storing metrics in dictionary
    evaluation_results[name] = {
        "RMSE": rmse,
        "MAE": mae,
        "R2": r2
    }

for name, model in models.items():
    evaluate_model(name, model, X_test, y_test)

# Printing  results
for m_name, metrics in evaluation_results.items():
    print(m_name, metrics)

# storing results in a json file
json_file_path = "evaluation_results.json"

with open(json_file_path, "w") as json_file:
    json.dump(evaluation_results, json_file, indent=4)

print(f"Evaluation metrics successfully saved to {json_file_path}")
```

```
LinearRegression {'RMSE': 0.7455813830127762, 'MAE': 0.5332001304956565, 'R2': 0.575787706032451}
DecisionTree {'RMSE': 0.7030445773467542, 'MAE': 0.4537843265503876, 'R2': 0.6228111330554302}
NeuralNetwork {'RMSE': 0.5072218293125931, 'MAE': 0.3387485704888966, 'R2': 0.8036689396950109}
XGBoost {'RMSE': 0.4717943691423984, 'MAE': 0.30957335413783094, 'R2': 0.8301370561019205}
Ridge {'RMSE': 0.7455542909384607, 'MAE': 0.5331933646313114, 'R2': 0.5758185345441323}
Evaluation metrics successfully saved to evaluation_results.json
```

Insights

- XGBoost excels at handling non-linearity and often performs best on tabular data, but can be more complex to tune.
- Neural Networks capture complex relationships but require careful tuning and scaling.
- Linear/Ridge regressions provide quick, interpretable baselines, though they may struggle with non-linear patterns.
- Decision Trees can capture non-linearities but often overfit if hyperparameters aren’t carefully managed.

In [10]:
```
# Saving the scaler
joblib.dump(scaler, f"{model_dir}/scaler.pkl")
```

Out[10]:
```
['models/scaler.pkl']
```