Part 2 — Prediction

Group 4

Wednesday 17th December, 2025

1 Part 2: House Prices Classification

Understanding the factors that influence housing prices is key in real estate analytics, urban planning, and financial decision-making. In this project, we analyze a comprehensive dataset of residential home sales from Ames, Iowa (Dean De Cock).

In part 2, we build a classification model by converting `SalePrice` into price categories (e.g., low / mid / high). We then apply a machine learning approach using classifiers.

We follow the following workflow:

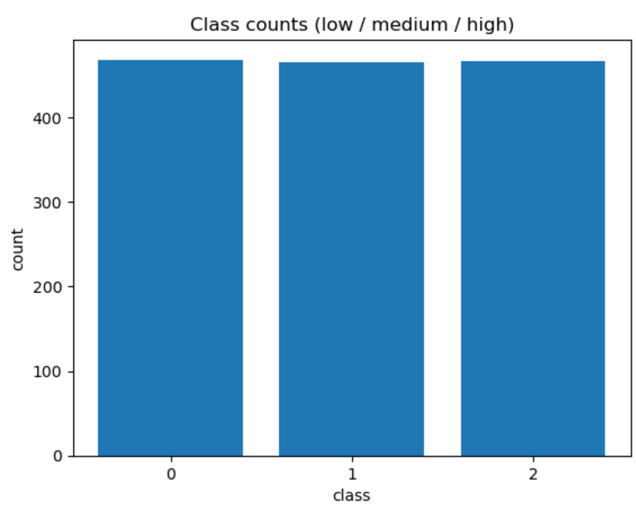
1. Load and inspect data
2. Clean + preprocess (handle missing values, encode categories)
3. Train models (Logistic Regression and Random Forest)
4. Evaluate using accuracy + confusion matrix
5. Fit best model and predict test labels
6. Show most predictive features of housing prices

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

from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
```

```
train_df = pd.read_csv("../Part1 -EDA/kaggledata/clean_train.csv")
test_df  = pd.read_csv("../Part1 -EDA/kaggledata/test.csv")
```

The SalePrice variable is continuous, so we convert it into discrete price classes. Here, we use three classes: low (0), medium (1), and high prices (2).

```
def make_price_classes(sale_price, n_bins=3):
    # equal -sized groups
    y = pd.qcut(sale_price, q=n_bins, labels=False, duplicates="drop").astype(int)

    bins = pd.qcut(sale_price, q=n_bins, duplicates="drop").cat.categories
    label_map = {i: f"{bins[i].left:.0f}-{bins[i].right:.0f}" for i in range(len(bins))}

    class_names = [f"class {i} ({label_map[i]})" for i in range(len(label_map))]
    return y, label_map, class_names

y, label_map, class_names = make_price_classes(train_df["SalePrice"], n_bins=3)

# plot distribution counts - do we have balance
counts = pd.Series(y).value_counts().sort_index()

plt.figure()
plt.bar(range(len(counts)), counts.values)
plt.xticks(range(len(counts)), [f"{i}" for i in counts.index])
plt.title("Class counts (low / medium / high)")
plt.xlabel("class")
plt.ylabel("count")
plt.savefig("Graphs/class_distribution_counts.png", bbox_inches="tight")
plt.show()
```



The class distribution appears to be balanced across low, medium, and high price categories, i.e. the classification task is well-suited for training and evaluation.

```
# split features
x = train_df.drop(columns=["SalePrice"]).copy()
test_x = test_df.copy()

# any columns with missing values?
print("total missing in x:", int(x.isna().sum().sum()))
print("total missing in test_x:", int(test_x.isna().sum().sum()))
```

```
total missing in x: 7310
total missing in test_x: 7878
```

```
# split missingness into numeric vs categorical columns
num_cols = x.select_dtypes(include=np.number).columns
cat_cols = x.select_dtypes(exclude=np.number).columns

na_num = x[num_cols].isna().sum()
na_num = na_num[na_num > 0].sort_values(ascending=False)

na_cat = x[cat_cols].isna().sum()
na_cat = na_cat[na_cat > 0].sort_values(ascending=False)

print("numeric columns with NaNs:")
display(na_num)

print("categorical columns with NaNs:")
display(na_cat)
```

```
numeric columns with NaNs:
```

```
GarageYrBlt    81
dtype: int64
```

```
categorical columns with NaNs:
```

```
PoolQC          1393
MiscFeature     1345
Alley           1308
Fence           1122
MasVnrType       861
FireplaceQu      689
GarageQual        81
GarageType        81
GarageFinish      81
```

```
GarageCond       81
BsmtExposure     38
BsmtFinType2     38
BsmtFinType1     37
BsmtQual         37
BsmtCond         37
dtype: int64
```

The remaining NaN values appear in both categorical and numeric features. Since sklearn models cannot run with NaNs, we can use reasonable two imputers: (1) categorical NaNs are filled with value “None”, (2) while numeric NaNs are filled with “0”.

```
num_cols = x.select_dtypes(include=np.number).columns
cat_cols = x.select_dtypes(exclude=np.number).columns

num_pipe = Pipeline([
    ("imputer", SimpleImputer(strategy="constant", fill_value=0))
])

cat_pipe = Pipeline([
    ("imputer", SimpleImputer(strategy="constant", fill_value="None")),
    ("onehot", OneHotEncoder(handle_unknown="ignore"))
])

preprocessor = ColumnTransformer(
    transformers=[
        ("num", num_pipe, num_cols),
        ("cat", cat_pipe, cat_cols),
    ],
    remainder="drop"
)

# training data / validation data - - keep 20% of the data for validation and stratify by pr
x_train, x_valid, y_train, y_valid = train_test_split(
    x,
    y,
    test_size=0.2,
    random_state=42,
    stratify=y
)

# evaluate our models : logistic regression + random forest
import sys
from pathlib import Path
sys.path.append(str(Path("..").resolve()))
```

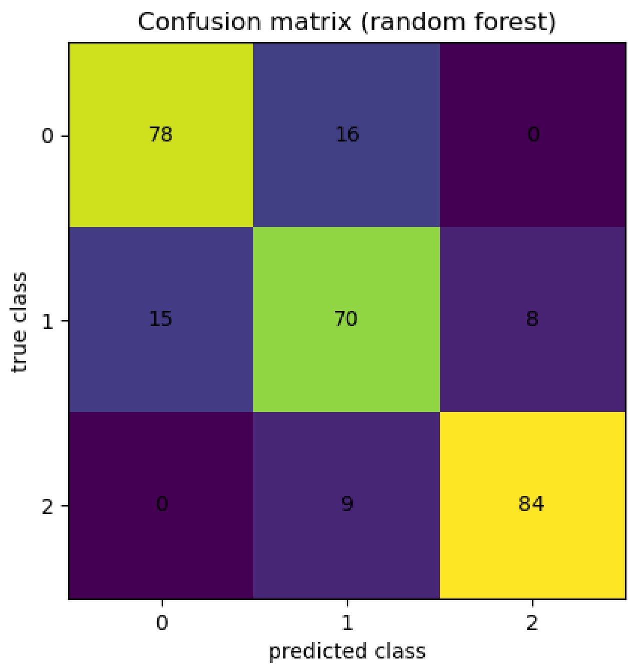
```
from src.models import _eval_model_core as eval_model

logistic_pipe = Pipeline([
    ("prep", preprocessor),
    ("model", LogisticRegression(max_iter=1000, class_weight="balanced"))
])

rf_pipe = Pipeline([
    ("prep", preprocessor),
    ("model", RandomForestClassifier(
        n_estimators=200,
        random_state=42,
        n_jobs=1,
        class_weight="balanced_subsample"
    ))
])

log_acc, log_cm = eval_model(
    "logistic regression",
    logistic_pipe,
    x_train, y_train,
    x_valid, y_valid,
    class_names,
)

rf_acc, rf_cm = eval_model(
    "random forest",
    rf_pipe,
    x_train, y_train,
    x_valid, y_valid,
    class_names,
)
```

```
/home/jovyan/.local/share/envs/final_env/lib/python3.11/site -packages/sklearn/linear_model/
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT

Increase the number of iterations to improve the convergence (max_iter=1000).
You might also want to scale the data as shown in:
    https://scikit -learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit -learn.org/stable/modules/linear_model.html#logistic -regression
  n_iter_i = _check_optimize_result(

============================================================
logistic regression
accuracy: 0.761
```

```
                          precision    recall  f1 -score   support

 class 0 (34900-138000)       0.84      0.74      0.79        94
class 1 (138000-185000)       0.64      0.69      0.66        93
class 2 (185000-340000)       0.81      0.85      0.83        93

               accuracy                           0.76       280
              macro avg       0.77      0.76      0.76       280
           weighted avg       0.77      0.76      0.76       280

============================================================
random forest
accuracy: 0.829

                          precision    recall  f1 -score   support

 class 0 (34900-138000)       0.84      0.83      0.83        94
class 1 (138000-185000)       0.74      0.75      0.74        93
class 2 (185000-340000)       0.91      0.90      0.91        93

               accuracy                           0.83       280
              macro avg       0.83      0.83      0.83       280
           weighted avg       0.83      0.83      0.83       280
```

Random forest achieves higher validation accuracy than logistic regression, so we use it for predictions below.

```
plt.figure()
plt.imshow(rf_cm)
plt.title("Confusion matrix (random forest)")
plt.xlabel("predicted class")
plt.ylabel("true class")
plt.xticks(range(3), [0, 1, 2])
plt.yticks(range(3), [0, 1, 2])

for i in range(rf_cm.shape[0]):
    for j in range(rf_cm.shape[1]):
        plt.text(j, i, str(rf_cm[i, j]), ha="center", va="center")

plt.savefig("Graphs/confusion_matrix.png", bbox_inches="tight")
plt.show()
```

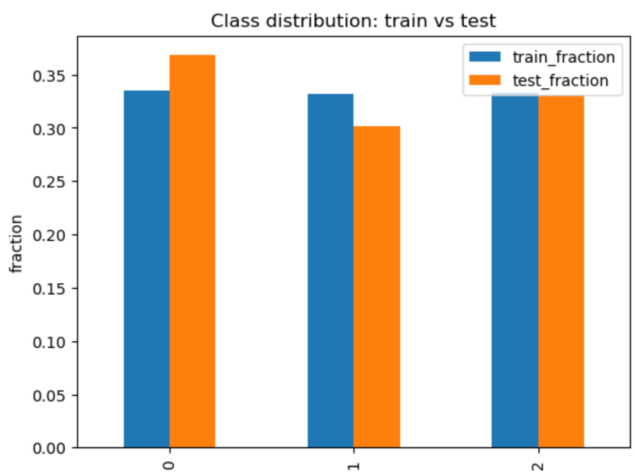


The confusion matrix compares true classes (i.e. the ground truth) to predicted classes and shows that most homes are classified correctly, with mistakes mainly between adjacent price groups.

```
# now fit random forest on full training df
rf_pipe.fit(x, y)
test_preds = rf_pipe.predict(test_x)
test_ids = test_df["Id"]

pred_df = pd.DataFrame({
    "Id": test_ids,
    "pred_class": test_preds,
    "pred_label": [label_map[i] for i in test_preds]
})

pred_df.head()
```

	Id	pred_class	pred_label
0	1461	0	34900–138000
1	1462	1	138000–185000
2	1463	1	138000–185000
3	1464	2	185000–340000
4	1465	1	138000–185000

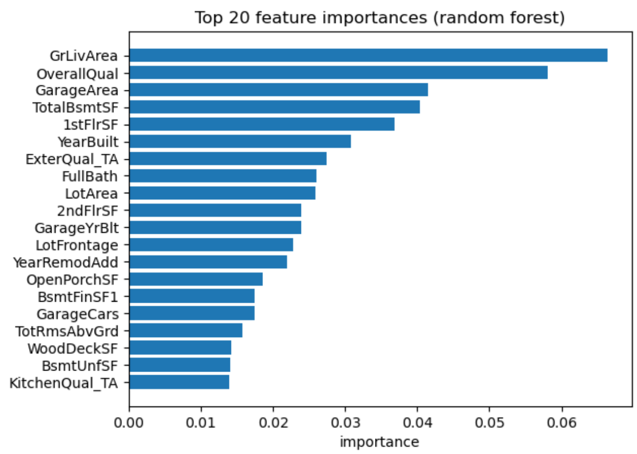
```
# let's compare predicted classes to training distribution - - pretty close!
train_dist = pd.Series(y).value_counts(normalize=True).sort_index()
test_dist  = pred_df["pred_class"].value_counts(normalize=True).sort_index()

dist_df = pd.DataFrame({
    "train_fraction": train_dist,
    "test_fraction": test_dist
})

dist_df

dist_df.plot(kind="bar")
plt.ylabel("fraction")
plt.title("Class distribution: train vs test")
plt.savefig("Graphs/class_distribution_train_vs_test.png", bbox_inches="tight")
plt.show()
```



The predicted class distribution on the test set is reasonably balanced and consistent with the training data, suggesting no obvious distribution shift in predictions. This is as expected.

```
rf_model = rf_pipe.named_steps["model"]

ohe = rf_pipe.named_steps["prep"].named_transformers_["cat"].named_steps["onehot"]
cat_feature_names = ohe.get_feature_names_out(cat_cols)
feature_names = np.concatenate([num_cols.astype(str), cat_feature_names])

importances = rf_model.feature_importances_
top_k = 20
idx = np.argsort(importances)[:: -1][:top_k]
```

```
plt.figure()
plt.barh(range(top_k), importances[idx][:: -1])
plt.yticks(range(top_k), feature_names[idx][:: -1])
plt.title("Top 20 feature importances (random forest)")
plt.xlabel("importance")
plt.savefig("Graphs/top_20_rf_features.png", bbox_inches="tight")
plt.show()
```



The most important features for predicting price category are higher-quality construction, larger living areas, better garage and basement characteristics, and how new the home is.