

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))}

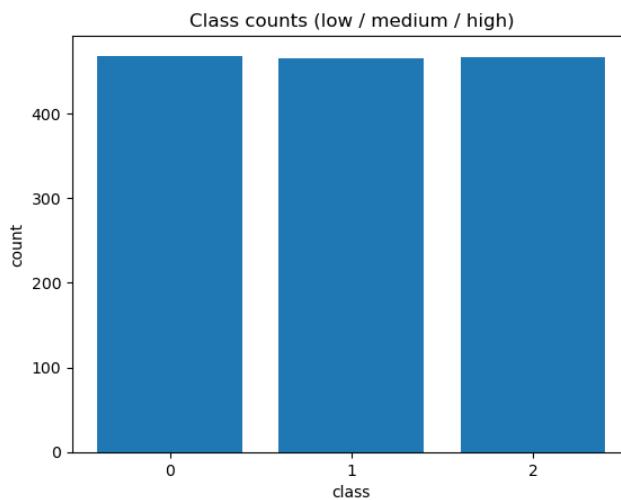
    class_names = [f"class {i} ({label_map[i]})" for i in range(len(label_map))]
    return y, label_map, class_names

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 price
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.

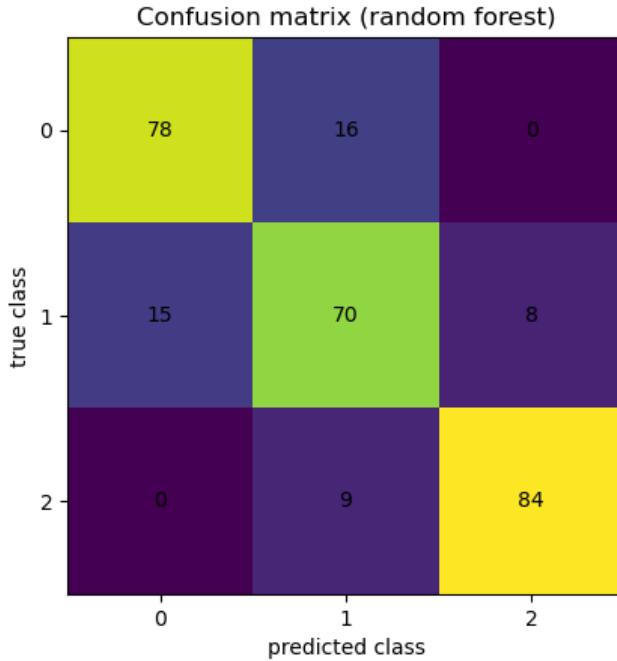
```

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

```

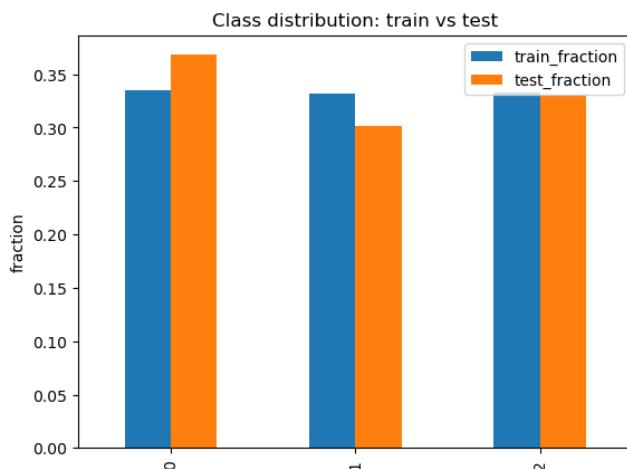
# let's compare predicted classes to training distribution -- pretty close!
train_dist = pd.Series(y).value_counts(normalize=True).sort_index()
test_dist = pred_df["pred_class"].value_counts(normalize=True).sort_index()

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])

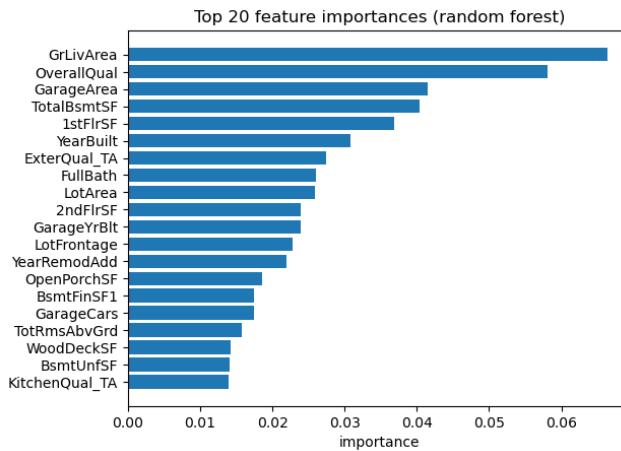
importances = rf_model.feature_importances_
top_k = 20
idx = np.argsort(importances)[:: -1][:top_k]

```

```

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.