MIDTERM_ITAI1371_Team_Decepticon_NOTEBOOK_Demel

October 27, 2025

0.1 Midterm: HR Data Preprocessing and Feature Engineering

This notebook prepares the Kaggle HR dataset, aug_train.csv, for supervised learning and predicts the target, which indicates whether a candidate is seeking a job change. We load the data without skipping lines, evaluate data quality, create a leakage-safe preprocessing pipeline, and assess baseline models while displaying before and after views of key steps.

Major Areas: - Data quality check and text standardization. - Ordinal conversions for experience, last new job, company size, and education level. - Imputation of missing values in a train-only pipeline. - Feature engineering for training intensity, job stability, and city by experience interaction. - Scaling and log normalization for numeric features. - One-hot encoding for nominal categories and city frequency encoding. - Splitting data into train and test sets, fitting the pipeline on training data only, and previewing processed features. - Baseline evaluation with logistic regression and a class-weighted variant, along with a concise run summary.

0.2 Section 0. Title and setup

We set up the environment for the HR dataset preprocessing and feature engineering workflow. We install core libraries, import dependencies, fix the random seed, configure plotting, and print library versions to make runs reproducible.

[1]:
```
import sys
!{sys.executable} -m pip install --quiet pandas numpy matplotlib seaborn␣
↪scikit-learn

import io
import warnings
from pathlib import Path

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from IPython.display import display, Markdown

from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScaler,␣
↪FunctionTransformer
```

```python
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    roc_auc_score,
    RocCurveDisplay,
)

RANDOM_STATE = 42
np.random.seed(RANDOM_STATE)

sns.set_theme(style="whitegrid")
plt.rcParams["figure.figsize"] = (10, 6)
plt.rcParams["axes.titlesize"] = 12
plt.rcParams["axes.labelsize"] = 11

warnings.filterwarnings("ignore", category=FutureWarning)

print(f"pandas version: {pd.__version__}")
print(f"numpy version: {np.__version__}")
print(f"seaborn version: {sns.__version__}")
print(f"matplotlib version: {plt.matplotlib.__version__}")
import sklearn
print(f"scikit-learn version: {sklearn.__version__}")
```

```
pandas version: 2.3.1
numpy version: 1.26.4
seaborn version: 0.13.2
matplotlib version: 3.10.5
scikit-learn version: 1.7.1
```

0.3 Section 1. Load data without skipping lines

We load aug_train.csv without skipping any lines and verify row counts. We display a preview, schema, target distribution, and check that enrollee_id is unique.

[2]:
```python
data_path = Path("aug_train.csv")

if not data_path.exists():
    raise FileNotFoundError("Expected aug_train.csv in the working directory.")

with data_path.open("r", encoding="utf-8") as f:
    raw_line_count = sum(1 for _ in f)
```

```python
df = pd.read_csv(data_path)
expected_rows = raw_line_count - 1
assert len(df) == expected_rows, f"Expected {expected_rows} rows but loaded␣
↪{len(df)}."

print(f"Loaded {len(df)} rows from {data_path.name} without skipping any lines.
↪")
print(f"Shape: {df.shape}")

display(df.head())
info_buffer = io.StringIO()
df.info(buf=info_buffer)
print(info_buffer.getvalue())

if "target" not in df.columns:
    raise KeyError("The target column is missing from the dataset.")

print("Target distribution:")
print(df["target"].value_counts(dropna=False).to_string())

duplicate_ids = df["enrollee_id"].duplicated().sum()
if duplicate_ids == 0:
    print("enrollee_id is unique.")
else:
    print(f"enrollee_id has {duplicate_ids} duplicates.")

initial_row_count = len(df)
target_col = "target"
id_col = "enrollee_id"
df_original = df.copy()
```

```
Loaded 19158 rows from aug_train.csv without skipping any lines.
Shape: (19158, 14)

   enrollee_id      city  city_development_index gender  \
0         8949  city_103                   0.920   Male
1        29725   city_40                   0.776   Male
2        11561   city_21                   0.624    NaN
3        33241  city_115                   0.789    NaN
4          666  city_162                   0.767   Male

       relevent_experience enrolled_university education_level  \
0  Has relevent experience       no_enrollment        Graduate
1   No relevent experience       no_enrollment        Graduate
2   No relevent experience    Full time course        Graduate
3   No relevent experience                 NaN        Graduate
4  Has relevent experience       no_enrollment         Masters
```

```
  major_discipline experience company_size    company_type last_new_job  \
0             STEM        >20          NaN             NaN            1
1             STEM         15        50-99         Pvt Ltd           >4
2             STEM          5          NaN             NaN        never
3  Business Degree         <1          NaN         Pvt Ltd        never
4             STEM        >20        50-99  Funded Startup            4

   training_hours  target
0              36     1.0
1              47     0.0
2              83     0.0
3              52     1.0
4               8     0.0
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19158 entries, 0 to 19157
Data columns (total 14 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   enrollee_id             19158 non-null  int64
 1   city                    19158 non-null  object
 2   city_development_index  19158 non-null  float64
 3   gender                  14650 non-null  object
 4   relevent_experience     19158 non-null  object
 5   enrolled_university     18772 non-null  object
 6   education_level         18698 non-null  object
 7   major_discipline        16345 non-null  object
 8   experience              19093 non-null  object
 9   company_size            13220 non-null  object
 10  company_type            13018 non-null  object
 11  last_new_job            18735 non-null  object
 12  training_hours          19158 non-null  int64
 13  target                  19158 non-null  float64
dtypes: float64(2), int64(2), object(10)
memory usage: 2.0+ MB

Target distribution:
target
0.0    14381
1.0     4777
enrollee_id is unique.
```

0.4 Section 2. Data quality assessment

We perform an initial data quality assessment. We summarize missing values, duplicates, data types, and cardinalities, and visualize missingness and two key numeric distributions.

[3]:

```
missing_counts = df.isna().sum()
missing_percent = (missing_counts / len(df)) * 100
missing_summary = pd.DataFrame({
    "missing_count": missing_counts,
    "missing_percent": missing_percent,
}).sort_values("missing_count", ascending=False)

duplicate_rows = df.duplicated().sum()
duplicate_enrollee_id = df[id_col].duplicated().sum()

numeric_columns = df.select_dtypes(include=[np.number]).columns.tolist()
categorical_columns = df.select_dtypes(include=["object"]).columns.tolist()

categorical_cardinality = pd.DataFrame({
    "unique_values": df[categorical_columns].nunique(dropna=True)
}).sort_values("unique_values", ascending=False)

numeric_describe = df[numeric_columns].describe()

print(f"Duplicate rows: {duplicate_rows}")
print(f"Duplicate enrollee_id values: {duplicate_enrollee_id}")

display(missing_summary)
display(categorical_cardinality)
display(numeric_describe)

plt.figure(figsize=(12, 6))
sns.heatmap(df.isna(), cbar=False)
plt.title("Missing Data Heatmap")
plt.xlabel("Columns")
plt.ylabel("Rows")
plt.show()

plt.figure(figsize=(12, 4))
missing_counts.plot(kind="bar")
plt.title("Missing Values by Column")
plt.ylabel("Count")
plt.xticks(rotation=45, ha="right")
plt.tight_layout()
plt.show()

fig, axes = plt.subplots(1, 2, figsize=(12, 4))
sns.histplot(df["training_hours"], bins=30, ax=axes[0], kde=False)
axes[0].set_title("Training Hours Distribution")
axes[0].set_xlabel("training_hours")

sns.histplot(df["city_development_index"], bins=30, ax=axes[1], kde=False)
```

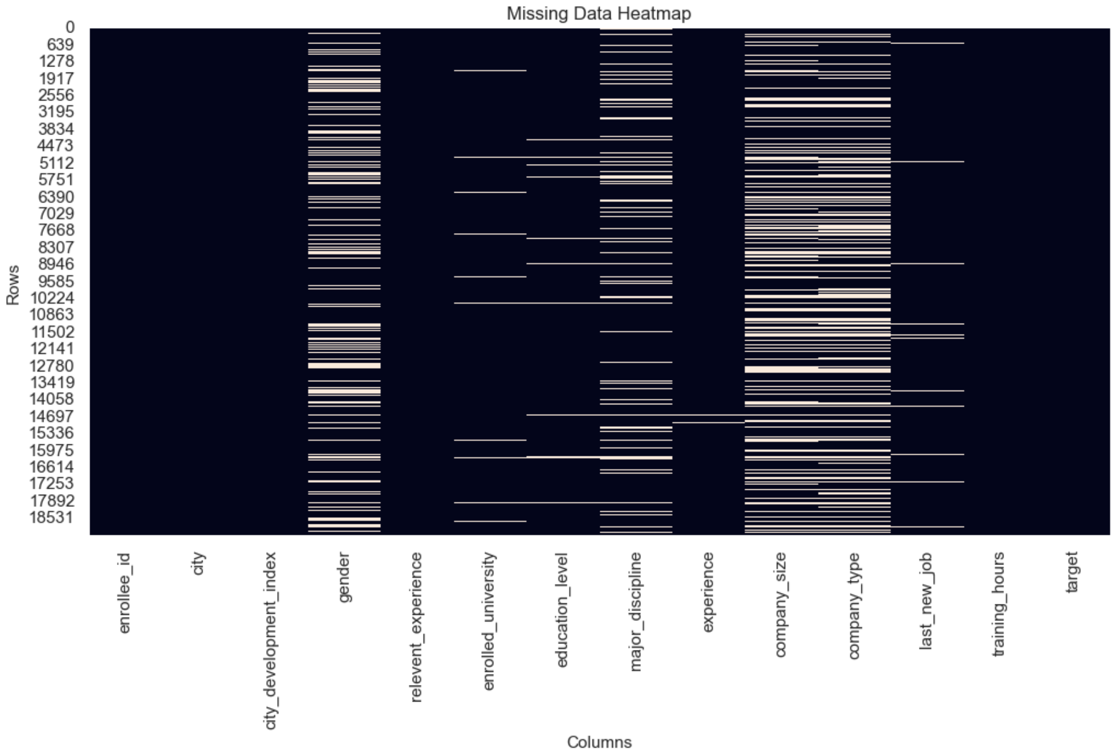
```
axes[1].set_title("City Development Index Distribution")
axes[1].set_xlabel("city_development_index")

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

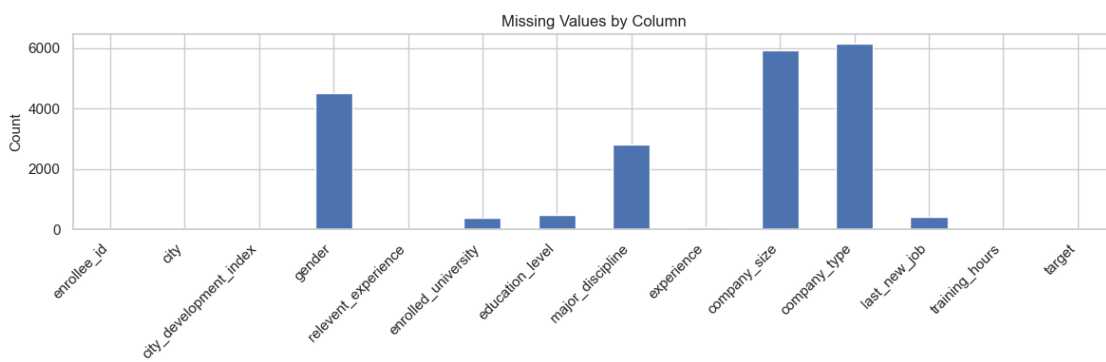
```
Duplicate rows: 0
Duplicate enrollee_id values: 0
```

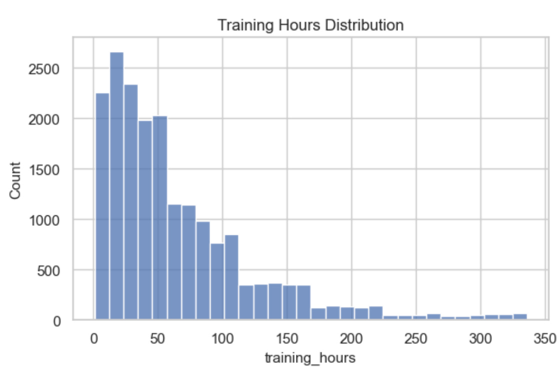
	missing_count	missing_percent
company_type	6140	32.049274
company_size	5938	30.994885
gender	4508	23.530640
major_discipline	2813	14.683161
education_level	460	2.401086
last_new_job	423	2.207955
enrolled_university	386	2.014824
experience	65	0.339284
enrollee_id	0	0.000000
city	0	0.000000
city_development_index	0	0.000000
relevent_experience	0	0.000000
training_hours	0	0.000000
target	0	0.000000

	unique_values
city	123
experience	22
company_size	8
major_discipline	6
company_type	6
last_new_job	6
education_level	5
gender	3
enrolled_university	3
relevent_experience	2

	enrollee_id	city_development_index	training_hours	target
count	19158.000000	19158.000000	19158.000000	19158.000000
mean	16875.358179	0.828848	65.366896	0.249348
std	9616.292592	0.123362	60.058462	0.432647
min	1.000000	0.448000	1.000000	0.000000
25%	8554.250000	0.740000	23.000000	0.000000
50%	16982.500000	0.903000	47.000000	0.000000
75%	25169.750000	0.920000	88.000000	0.000000
max	33380.000000	0.949000	336.000000	1.000000


Missing Data Heatmap
Rows
Columns
enrollee_id
city
city_development_index
gender
relevent_experience
enrolled_university
education_level
major_discipline
experience
company_size
company_type
last_new_job
training_hours
target


Missing Values by Column
Count


Training Hours Distribution
Count
training_hours


City Development Index Distribution
Count
city_development_index

0.5 Section 3. Target and feature definition

We define the supervised target and the initial feature set. We keep the identifier separate and do not use it as a feature.

[4]:
```
feature_cols = [
    "city",
    "city_development_index",
    "gender",
    "relevent_experience",
    "enrolled_university",
    "education_level",
    "major_discipline",
    "experience",
    "company_size",
    "company_type",
    "last_new_job",
    "training_hours",
]

base_feature_count = len(feature_cols)
print(f"Features selected ({base_feature_count} columns):")
print(feature_cols)
```

```
Features selected (12 columns):
['city', 'city_development_index', 'gender', 'relevent_experience',
'enrolled_university', 'education_level', 'major_discipline', 'experience',
'company_size', 'company_type', 'last_new_job', 'training_hours']
```

0.6 Section 4. Clean raw categorical text and fix inconsistencies

We standardize categorical text, align common variants, and show before-and-after samples with value-count comparisons.

[5]:
```
text_columns = df[feature_cols].select_dtypes(include="object").columns.tolist()
text_preview_before = df[text_columns].head(5).copy()
text_before = df[text_columns].copy()

def standardize_text(series):
    return series.str.strip().str.lower()

df[text_columns] = df[text_columns].apply(lambda col: standardize_text(col) if␣
↪col.dtype == object else col)

company_size_replacements = {
    "oct-49": "10/49",
```

```python
    "10-49": "10/49",
    "10 / 49": "10/49",
    "10 to 49": "10/49",
    "10\49": "10/49",
}
df["company_size"] = df["company_size"].replace(company_size_replacements)

enrolled_map = {
    "no enrollment": "no_enrollment",
    "no_enrollment": "no_enrollment",
    "full time course": "full_time_course",
    "full_time_course": "full_time_course",
    "part time course": "part_time_course",
    "part_time_course": "part_time_course",
}
df["enrolled_university"] = df["enrolled_university"].replace(enrolled_map)

gender_map = {
    "m": "male",
    "male": "male",
    "f": "female",
    "female": "female",
}
df["gender"] = df["gender"].replace(gender_map)
df.loc[df["gender"].notna() & ~df["gender"].isin(["male", "female", "other"]),␣
 ↪"gender"] = "other"

text_after = df[text_columns].copy()
text_corrections = int(((text_before != text_after) & ~(text_before.isna() &␣
 ↪text_after.isna())).sum().sum())
print(f"Text normalisation adjustments applied to {text_corrections} values.")

comparison_preview = pd.concat([text_preview_before, df[text_columns].head(5)],␣
 ↪axis=1, keys=["before", "after"])
display(comparison_preview)

for col in ["company_size", "enrolled_university", "gender"]:
    before_counts = text_before[col].value_counts(dropna=False)
    after_counts = text_after[col].value_counts(dropna=False)
    counts_df = pd.concat([before_counts, after_counts], axis=1,␣
 ↪keys=["before", "after"]).fillna(0).astype(int)
    print(f"Value counts before vs after for {col}:")
    display(counts_df)
```

```
Text normalisation adjustments applied to 86824 values.

     before                                                    \
       city gender      relevent_experience enrolled_university
```

```
0  city_103   Male  Has relevent experience       no_enrollment
1   city_40   Male   No relevent experience       no_enrollment
2   city_21    NaN   No relevent experience    Full time course
3  city_115    NaN   No relevent experience                 NaN
4  city_162   Male  Has relevent experience       no_enrollment

                                                                          \
  education_level major_discipline experience company_size    company_type
0        Graduate             STEM        >20          NaN             NaN
1        Graduate             STEM         15        50-99         Pvt Ltd
2        Graduate             STEM          5          NaN             NaN
3        Graduate  Business Degree         <1          NaN         Pvt Ltd
4         Masters             STEM        >20        50-99  Funded Startup

                    after                                                   \
  last_new_job      city gender      relevent_experience enrolled_university
0            1  city_103   male  has relevent experience       no_enrollment
1           >4   city_40   male   no relevent experience       no_enrollment
2        never   city_21    NaN   no relevent experience    full_time_course
3        never  city_115    NaN   no relevent experience                 NaN
4            4  city_162   male  has relevent experience       no_enrollment

                                                                          \
  education_level major_discipline experience company_size    company_type
0        graduate             stem        >20          NaN             NaN
1        graduate             stem         15        50-99         pvt ltd
2        graduate             stem          5          NaN             NaN
3        graduate  business degree         <1          NaN         pvt ltd
4         masters             stem        >20        50-99  funded startup


  last_new_job
0            1
1           >4
2        never
3        never
4            4

Value counts before vs after for company_size:

              before  after
company_size
NaN             5938   5938
50-99           3083   3083
100-500         2571   2571
10000+          2019   2019
10/49           1471   1471
1000-4999       1328   1328
<10             1308   1308
```

```
500-999          877    877
5000-9999        563    563
```

```
Value counts before vs after for enrolled_university:
```

```
                     before  after
enrolled_university
no_enrollment         13817  13817
Full time course       3757      0
Part time course       1198      0
NaN                     386    386
full_time_course          0   3757
part_time_course          0   1198
```

```
Value counts before vs after for gender:
```

```
        before  after
gender
Male     13221      0
NaN       4508   4508
Female    1238      0
Other      191      0
male         0  13221
female       0   1238
other        0    191
```

0.7 Section 5. Type conversions for ordinal-like fields

We convert ordered categories to numbers for modeling. We add derived fields for experience, time since last job change, company size, and education level, and preview the mappings.

[6]:

```
experience_map = {
    "<1": 0.5,
    "0": 0,
    "1": 1,
    "2": 2,
    "3": 3,
    "4": 4,
    "5": 5,
    "6": 6,
    "7": 7,
    "8": 8,
    "9": 9,
    "10": 10,
    "11": 11,
    "12": 12,
    "13": 13,
    "14": 14,
    "15": 15,
    "16": 16,
```

```
    "17": 17,
    "18": 18,
    "19": 19,
    "20": 20,
    ">20": 21,
}
df["experience_years"] = df["experience"].map(experience_map)

last_new_job_map = {
    "never": 0,
    "0": 0,
    "1": 1,
    "2": 2,
    "3": 3,
    "4": 4,
    ">4": 5,
}
df["last_new_job_years"] = df["last_new_job"].map(last_new_job_map)

company_size_order = ["<10", "10/49", "50-99", "100-500", "500-999",
 ↪"1000-4999", "5000-9999", "10000+"]
company_size_mid = {
    "<10": 5,
    "10/49": 30,
    "50-99": 75,
    "100-500": 300,
    "500-999": 750,
    "1000-4999": 3000,
    "5000-9999": 7500,
    "10000+": 10000,
}
df["company_size_ordered"] = pd.Categorical(df["company_size"],
 ↪categories=company_size_order, ordered=True)
df["company_size_num"] = df["company_size"].map(company_size_mid)

education_map = {
    "primary school": 0,
    "high school": 1,
    "graduate": 2,
    "masters": 3,
    "phd": 4,
}
df["education_level_ordinal"] = df["education_level"].map(education_map)

derived_features = [
    "experience_years",
    "last_new_job_years",
```

```
    "company_size_num",
    "education_level_ordinal",
]
for col in derived_features:
    if col not in feature_cols:
        feature_cols.append(col)

conversion_preview = df[[
    "experience", "experience_years",
    "last_new_job", "last_new_job_years",
    "company_size", "company_size_num",
    "education_level", "education_level_ordinal",
]].head(10)
display(conversion_preview)
```

```
  experience  experience_years last_new_job  last_new_job_years company_size  \
0        >20              21.0            1                 1.0          NaN
1         15              15.0           >4                 5.0        50-99
2          5               5.0        never                 0.0          NaN
3         <1               0.5        never                 0.0          NaN
4        >20              21.0            4                 4.0        50-99
5         11              11.0            1                 1.0          NaN
6          5               5.0            1                 1.0        50-99
7         13              13.0           >4                 5.0          <10
8          7               7.0            1                 1.0        50-99
9         17              17.0           >4                 5.0       10000+

   company_size_num education_level  education_level_ordinal
0               NaN        graduate                      2.0
1              75.0        graduate                      2.0
2               NaN        graduate                      2.0
3               NaN        graduate                      2.0
4              75.0         masters                      3.0
5               NaN        graduate                      2.0
6              75.0     high school                      1.0
7               5.0        graduate                      2.0
8              75.0        graduate                      2.0
9           10000.0        graduate                      2.0
```

0.8 Section 6. Missing value analysis and imputation plan

We quantify missing values for the modeling columns and illustrate median and mode imputation on a demo copy only. The original dataframe keeps its NaNs so the real imputation occurs inside the train-only pipeline and remains leakage-safe. We record counts for the summary.

[7]:
```
numeric_impute_cols = [
    "city_development_index",
    "training_hours",
```

```python
    "experience_years",
    "last_new_job_years",
    "company_size_num",
    "education_level_ordinal",
]

categorical_impute_cols = [
    "city",
    "gender",
    "relevent_experience",
    "enrolled_university",
    "major_discipline",
    "company_type",
]

imputation_targets = numeric_impute_cols + categorical_impute_cols

# Count missing values BEFORE (on the real df)
missing_before = df[imputation_targets].isna().sum()

# Demo-only copy for illustrations so we do not leak test information
df_imputation_demo = df.copy(deep=True)

# Numeric: median on the demo copy
numeric_impute_values = {}
for col in numeric_impute_cols:
    med = df_imputation_demo[col].median()
    numeric_impute_values[col] = med
    df_imputation_demo[col] = df_imputation_demo[col].fillna(med)

# Categorical: mode on the demo copy
categorical_impute_values = {}
for col in categorical_impute_cols:
    mode_series = df_imputation_demo[col].mode(dropna=True)
    mode_val = mode_series.iloc[0] if not mode_series.empty else "missing"
    categorical_impute_values[col] = mode_val
    df_imputation_demo[col] = df_imputation_demo[col].fillna(mode_val)

# Count missing values AFTER (still on the demo copy)
missing_after = df_imputation_demo[imputation_targets].isna().sum()

# Totals for Section 13 summary
missing_before_total = int(missing_before.sum())
missing_after_total = int(missing_after.sum())

print("Missing values BEFORE imputation (real df):")
display(missing_before.to_frame(name="missing_count_before"))
```

```python
print("Missing values AFTER imputation (demo copy):")
display(missing_after.to_frame(name="missing_count_after"))

assert missing_after_total == 0, "Imputation demo failed to resolve all missing␣
↪values."
print("All missing values filled in the imputation demo copy. The original df␣
↪retains NaNs for pipeline-based imputation.")
```

```
Missing values BEFORE imputation (real df):

                        missing_count_before
city_development_index                     0
training_hours                             0
experience_years                          65
last_new_job_years                       423
company_size_num                        5938
education_level_ordinal                  460
city                                       0
gender                                  4508
relevent_experience                        0
enrolled_university                      386
major_discipline                        2813
company_type                            6140

Missing values AFTER imputation (demo copy):

                        missing_count_after
city_development_index                    0
training_hours                            0
experience_years                          0
last_new_job_years                        0
company_size_num                          0
education_level_ordinal                   0
city                                      0
gender                                    0
relevent_experience                       0
enrolled_university                       0
major_discipline                          0
company_type                              0

All missing values filled in the imputation demo copy. The original df retains
NaNs for pipeline-based imputation.
```

0.9 Section 7. One hot and ordinal encoding setup

We define the columns for numeric and categorical processing and register custom transformers used later in the pipeline.

[8]:
```
numeric_features = [
    "city_development_index",
    "training_hours",
    "experience_years",
    "last_new_job_years",
    "company_size_num",
    "education_level_ordinal",
]

categorical_features = [
    "city",
    "gender",
    "relevent_experience",
    "enrolled_university",
    "major_discipline",
    "company_type",
]

model_input_features = numeric_features + categorical_features

print("Numeric features:")
print(numeric_features)
print("Categorical features:")
print(categorical_features)

# Custom transformers for leakage-safe preprocessing
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.utils.validation import check_is_fitted

class IQRCapper(BaseEstimator, TransformerMixin):
    def __init__(self, columns, factor=1.5):
        self.columns = columns
        self.factor = factor

    def fit(self, X, y=None):
        self.bounds_ = {}
        X_ = pd.DataFrame(X, columns=self.columns) if not isinstance(X, pd.
↪DataFrame) else X
        for col in self.columns:
            q1 = X_[col].quantile(0.25)
            q3 = X_[col].quantile(0.75)
            iqr = q3 - q1
            self.bounds_[col] = (q1 - self.factor * iqr, q3 + self.factor * iqr)
        return self

    def transform(self, X):
        check_is_fitted(self, "bounds_")
```

```python
        X_ = X.copy()
        for col, (lo, hi) in self.bounds_.items():
            X_[col] = X_[col].clip(lo, hi)
        return X_

    def get_feature_names_out(self, input_features=None):
        if input_features is None:
            return np.asarray(self.columns)
        return np.asarray(input_features)

class CityFrequencyEncoder(BaseEstimator, TransformerMixin):
    def __init__(self, column):
        self.column = column

    def fit(self, X, y=None):
        X_ = X if isinstance(X, pd.DataFrame) else pd.DataFrame(X,␣
↪columns=[self.column])
        self.freq_ = X_[self.column].value_counts()
        return self

    def transform(self, X):
        check_is_fitted(self, "freq_")
        X_ = X.copy()
        X_["city_frequency"] = X_[self.column].map(self.freq_).fillna(0).
↪astype(float)
        return X_[["city_frequency"]]

    def get_feature_names_out(self, input_features=None):
        return np.asarray(["city_frequency"])

class Log1pTransformer(FunctionTransformer):
    def __init__(self, columns):
        self.columns = columns
        super().__init__(self._log1p, validate=False)

    def _log1p(self, X):
        X = X.copy()
        X[self.columns] = np.log1p(X[self.columns])
        return X

    def get_feature_names_out(self, input_features=None):
        if input_features is None:
            return np.asarray(self.columns)
        return np.asarray(input_features)
```

```
Numeric features:
['city_development_index', 'training_hours', 'experience_years',
```

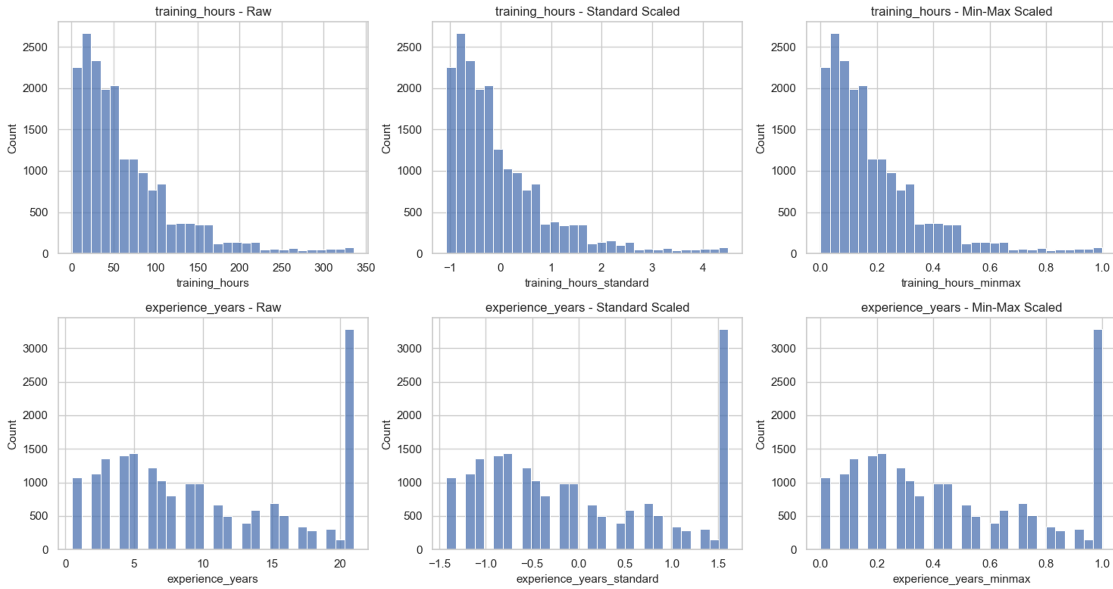
```
'last_new_job_years', 'company_size_num', 'education_level_ordinal']
Categorical features:
['city', 'gender', 'relevent_experience', 'enrolled_university',
'major_discipline', 'company_type']
```

0.10 Section 8. Scaling and normalization comparison

We compare raw distributions with standard and min-max scaling for two numeric features to motivate our choice. The final pipeline uses standard scaling.

[9]:
```python
scale_features = ["training_hours", "experience_years"]
scaler_standard = StandardScaler()
scaler_minmax = MinMaxScaler()

# Fit scalers on df for visualization; the live pipeline handles imputation on␣
↪X_train
standard_scaled = pd.DataFrame(
    scaler_standard.fit_transform(df[scale_features]),
    columns=[f"{col}_standard" for col in scale_features],
)

minmax_scaled = pd.DataFrame(
    scaler_minmax.fit_transform(df[scale_features]),
    columns=[f"{col}_minmax" for col in scale_features],
)

# Plot raw vs. scaled side-by-side
fig, axes = plt.subplots(len(scale_features), 3, figsize=(15, 8))

for idx, feature in enumerate(scale_features):
    # Raw
    sns.histplot(df[feature], bins=30, ax=axes[idx, 0], kde=False)
    axes[idx, 0].set_title(f"{feature} - Raw")
    axes[idx, 0].set_xlabel(feature)

    # Standard scaled
    sns.histplot(standard_scaled[f"{feature}_standard"], bins=30, ax=axes[idx,␣
↪1], kde=False)
    axes[idx, 1].set_title(f"{feature} - Standard Scaled")
    axes[idx, 1].set_xlabel(f"{feature}_standard")

    # Min-max scaled
    sns.histplot(minmax_scaled[f"{feature}_minmax"], bins=30, ax=axes[idx, 2],␣
↪kde=False)
    axes[idx, 2].set_title(f"{feature} - Min-Max Scaled")
    axes[idx, 2].set_xlabel(f"{feature}_minmax")

plt.tight_layout()
```

```
plt.show()
```

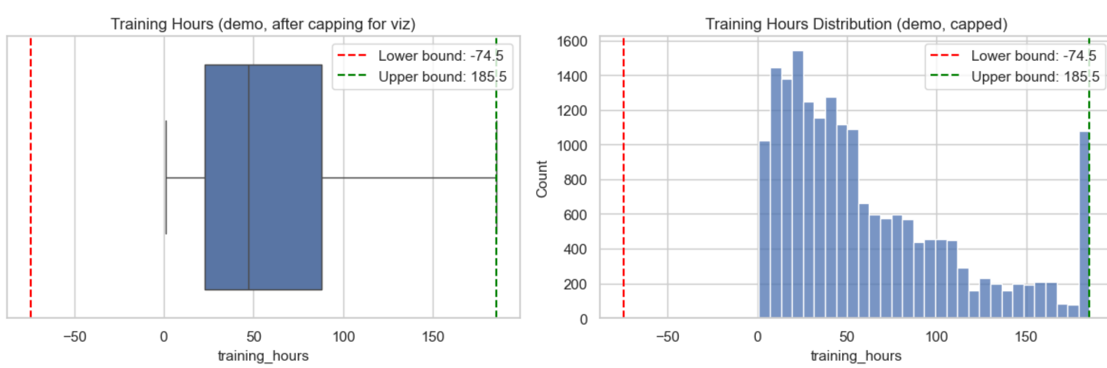


0.11 Section 9. Outlier detection and capping

We estimate outlier bounds with IQR and illustrate capping on a demo copy for visualization. The dataset used for modeling is not modified here. Robust capping is applied inside the train-only pipeline.

[10]:
```
def calculate_iqr_bounds(series, factor=1.5):
    q1 = series.quantile(0.25)
    q3 = series.quantile(0.75)
    iqr = q3 - q1
    lower_bound = q1 - factor * iqr
    upper_bound = q3 + factor * iqr
    return lower_bound, upper_bound

features_to_cap = ["training_hours", "experience_years"]
outlier_summary = {}
df_outlier_demo = df[features_to_cap].copy()

for feature in features_to_cap:
    lower, upper = calculate_iqr_bounds(df_outlier_demo[feature])
    below = int((df_outlier_demo[feature] < lower).sum())
    above = int((df_outlier_demo[feature] > upper).sum())
    outlier_summary[feature] = {
        "lower_bound": lower, "upper_bound": upper,
        "capped_below_demo": below, "capped_above_demo": above,
    }
```

```python
    # demo capping for visualization only
    df_outlier_demo[feature] = df_outlier_demo[feature].clip(lower=lower, upper=upper)

training_lower = outlier_summary["training_hours"]["lower_bound"]
training_upper = outlier_summary["training_hours"]["upper_bound"]

fig, axes = plt.subplots(1, 2, figsize=(12, 4))
sns.boxplot(x=df_outlier_demo["training_hours"], ax=axes[0])
axes[0].set_title("Training Hours (demo, after capping for viz)")
axes[0].axvline(training_lower, color="red", linestyle="--", label=f"Lower bound: {training_lower:.1f}")
axes[0].axvline(training_upper, color="green", linestyle="--", label=f"Upper bound: {training_upper:.1f}")
axes[0].legend()

sns.histplot(df_outlier_demo["training_hours"], bins=30, ax=axes[1], kde=False)
axes[1].axvline(training_lower, color="red", linestyle="--", label=f"Lower bound: {training_lower:.1f}")
axes[1].axvline(training_upper, color="green", linestyle="--", label=f"Upper bound: {training_upper:.1f}")
axes[1].set_title("Training Hours Distribution (demo, capped)")
axes[1].set_xlabel("training_hours")
axes[1].legend()

plt.tight_layout()
plt.show()

outlier_summary_df = pd.DataFrame(outlier_summary).T
print("Outlier (demo) summary for visualization:")
display(outlier_summary_df)
print("Note: The dataset itself is NOT modified here. Robust capping is implemented inside the pipeline.")
```



```
Outlier (demo) summary for visualization:

                   lower_bound  upper_bound  capped_below_demo  \
training_hours           -74.5        185.5                0.0
experience_years         -14.0         34.0                0.0

                   capped_above_demo
training_hours                 984.0
experience_years                 0.0

Note: The dataset itself is NOT modified here. Robust capping is implemented
inside the pipeline.
```

0.12 Section 10. Feature engineering

We add three domain features inside the train-fit pipeline to avoid leakage. The features are training_intensity, job_stability, and city_exp_interaction. They are created from existing columns with simple, interpretable formulas. We preview a few rows to confirm the shapes, and Section 11 consumes these features in the ColumnTransformer.

[11]:
```python
from sklearn.base import BaseEstimator, TransformerMixin

class DomainFeatureEngineer(BaseEstimator, TransformerMixin):
    """Create HR-specific features safely inside the pipeline.

    Features:
      training_intensity   = training_hours / (experience_years + 1)
      job_stability        = experience_years / (last_new_job_years + 1)
      city_exp_interaction= city_development_index * experience_years
    """
    def __init__(self):
        self._engineered_names = [
            "training_intensity",
            "job_stability",
            "city_exp_interaction",
        ]

    def fit(self, X, y=None):
        required = [
            "training_hours",
            "experience_years",
            "last_new_job_years",
            "city_development_index",
        ]
        missing = [c for c in required if c not in X.columns]
        if missing:
            raise ValueError(f"Missing required columns for feature engineering:
 ↪ {missing}")
        return self
```

```python
    def transform(self, X):
        X = X.copy()
        eps = 1e-8

        X["training_intensity"] = (
            X["training_hours"].fillna(0.0) / (X["experience_years"].fillna(0.
↪0) + 1.0 + eps)
        ).clip(0, 100)

        X["job_stability"] = (
            X["experience_years"].fillna(0.0) / (X["last_new_job_years"].
↪fillna(0.0) + 1.0 + eps)
        ).clip(0, 20)

        X["city_exp_interaction"] = (
            X["city_development_index"].fillna(0.5) * X["experience_years"].
↪fillna(0.0)
        )

        return X

    def get_feature_names_out(self, input_features=None):
        base = list(input_features) if input_features is not None else []
        return np.asarray(base + self._engineered_names)

# Preview the engineered columns on a few rows
_preview_cols = ["training_hours", "experience_years", "last_new_job_years",␣
↪"city_development_index"]
_preview = df[[c for c in _preview_cols if c in df.columns]].head(5).copy()
display(
    DomainFeatureEngineer()
    .fit(_preview)
    .transform(_preview)[["training_intensity", "job_stability",␣
↪"city_exp_interaction"]]
)
```

	training_intensity	job_stability	city_exp_interaction
0	1.636364	10.5	19.3200
1	2.937500	2.5	11.6400
2	13.833333	5.0	3.1200
3	34.666666	0.5	0.3945
4	0.363636	4.2	16.1070

0.13 Section 11. Final preprocessing pipeline and transformation

We assemble the end-to-end preprocessing pipeline. We engineer features first, then apply column-wise transforms with outlier capping, log normalization, imputation, scaling, one-hot encoding, and city frequency encoding. We fit on the training split only, transform both splits, and preview the processed matrix.

[12]:
```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer

# Base numeric and categorical inputs from earlier sections
numeric_features_base = [
    "city_development_index",
    "training_hours",
    "experience_years",
    "last_new_job_years",
    "company_size_num",
    "education_level_ordinal",
]

categorical_features = [
    "city",
    "gender",
    "relevent_experience",
    "enrolled_university",
    "major_discipline",
    "company_type",
]

# Engineered numeric features created by DomainFeatureEngineer
engineered_numeric = ["training_intensity", "job_stability",␣
↪"city_exp_interaction"]

# Full numeric feature list consumed by the ColumnTransformer
numeric_features_all = numeric_features_base + engineered_numeric

# Numeric pipeline: cap on raw drivers only; normalize skew on training_hours;␣
↪impute and scale
numeric_transformer = Pipeline(steps=[
    ("cap",   IQRCapper(columns=["training_hours", "experience_years"],␣
↪factor=1.5)),
    ("log1p", Log1pTransformer(columns=["training_hours"])),
    ("imputer", SimpleImputer(strategy="median")),
    ("scaler",  StandardScaler()),
])

# Categorical pipeline: impute then one-hot with infrequent bucket
categorical_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="most_frequent")),
```

```
    ("encoder", OneHotEncoder(
        drop="first",
        handle_unknown="infrequent_if_exist",
        min_frequency=5,
        sparse_output=False
    )),
])

# City frequency branch: frequency then scale
city_freq_pipeline = Pipeline(steps=[
    ("cityfreq", CityFrequencyEncoder(column="city")),
    ("scaler",   StandardScaler()),
])

# Column-wise mapper that expects engineered features already present
column_mapper = ColumnTransformer(
    transformers=[
        ("num",      numeric_transformer, numeric_features_all),
        ("cat",      categorical_transformer, categorical_features),
        ("cityfreq", city_freq_pipeline, ["city"]),
    ],
    remainder="drop",
)

# End-to-end preprocessor: engineer first, then column mapping
preprocessor = Pipeline(steps=[
    ("engineer", DomainFeatureEngineer()),
    ("columns",  column_mapper),
])

# Build X and y, then stratified split
# Note: city is routed to two branches (OHE and frequency), so we include it in
 ↪inputs
model_input = list(set(numeric_features_base + categorical_features + ["city"]))
X = df[model_input].copy()
y = df[target_col].astype(int).copy()

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.20, random_state=RANDOM_STATE, stratify=y
)

# Fit on training only; transform both splits
preprocessor.fit(X_train)
X_train_processed = preprocessor.transform(X_train)
X_test_processed  = preprocessor.transform(X_test)

# Names and a small before/after preview
```

```python
feature_names = preprocessor.named_steps["columns"].get_feature_names_out()
feature_count_after = len(feature_names)

processed_train_df = pd.DataFrame(X_train_processed, columns=feature_names)

preview_cols = ["city", "training_hours", "experience_years", "company_size",␣
 ↪"gender"]
preview_cols = [c for c in preview_cols if c in X_train.columns]

original_preview  = X_train[preview_cols].head().reset_index(drop=True)
processed_preview = processed_train_df.head().reset_index(drop=True)
comparison_table  = pd.concat([original_preview, processed_preview], axis=1)

print(f"Total features after preprocessing: {feature_count_after}")
display(pd.DataFrame({"feature_name": feature_names[:10]}))
display(comparison_table)
```

```
Total features after preprocessing: 133
```

```
/Users/martin.demel/myenv3.10/lib/python3.10/site-
packages/sklearn/preprocessing/_encoders.py:246: UserWarning: Found unknown
categories in columns [0] during transform. These unknown categories will be
encoded as all zeros
  warnings.warn(
```

```
                  feature_name
0   num__city_development_index
1           num__training_hours
2         num__experience_years
3       num__last_new_job_years
4         num__company_size_num
5  num__education_level_ordinal
6       num__training_intensity
7            num__job_stability
8     num__city_exp_interaction
9              cat__city_city_10
```

```
       city  training_hours  experience_years  gender  \
0   city_21              90              10.0     NaN
1  city_103              15               5.0    male
2   city_50              36              12.0    male
3  city_103              53               5.0    male
4   city_67             158               5.0  female

   num__city_development_index  num__training_hours  num__experience_years  \
0                    -1.672102             0.786600              -0.020180
1                     0.734358            -1.095313              -0.759569
2                     0.539240            -0.187708               0.275575
3                     0.734358             0.221599              -0.759569
```

```
4                    0.205913            1.390759              -0.759569

   num__last_new_job_years  num__company_size_num  \
0                -0.589366              -0.500260
1                -1.189700              -0.429925
2                 1.811969               0.414097
3                -0.589366              -0.429925
4                -0.589366              -0.429925

   num__education_level_ordinal  …  cat__major_discipline_humanities  \
0                     -0.194616  …                               0.0
1                     -3.113096  …                               0.0
2                     -0.194616  …                               0.0
3                     -0.194616  …                               0.0
4                     -0.194616  …                               0.0

   cat__major_discipline_no major  cat__major_discipline_other  \
0                             0.0                          0.0
1                             0.0                          0.0
2                             0.0                          0.0
3                             0.0                          0.0
4                             0.0                          0.0

   cat__major_discipline_stem  cat__company_type_funded startup  \
0                         1.0                               0.0
1                         1.0                               0.0
2                         1.0                               0.0
3                         1.0                               1.0
4                         1.0                               0.0

   cat__company_type_ngo  cat__company_type_other  \
0                    0.0                      0.0
1                    0.0                      0.0
2                    1.0                      0.0
3                    0.0                      0.0
4                    0.0                      0.0

   cat__company_type_public sector  cat__company_type_pvt ltd  \
0                              0.0                        1.0
1                              0.0                        1.0
2                              0.0                        0.0
3                              0.0                        0.0
4                              0.0                        1.0

   cityfreq__city_frequency
0                  0.570582
1                  1.591095
2                 -0.937386
```

```
3                   1.591095
4                  -0.760945

[5 rows x 137 columns]
```

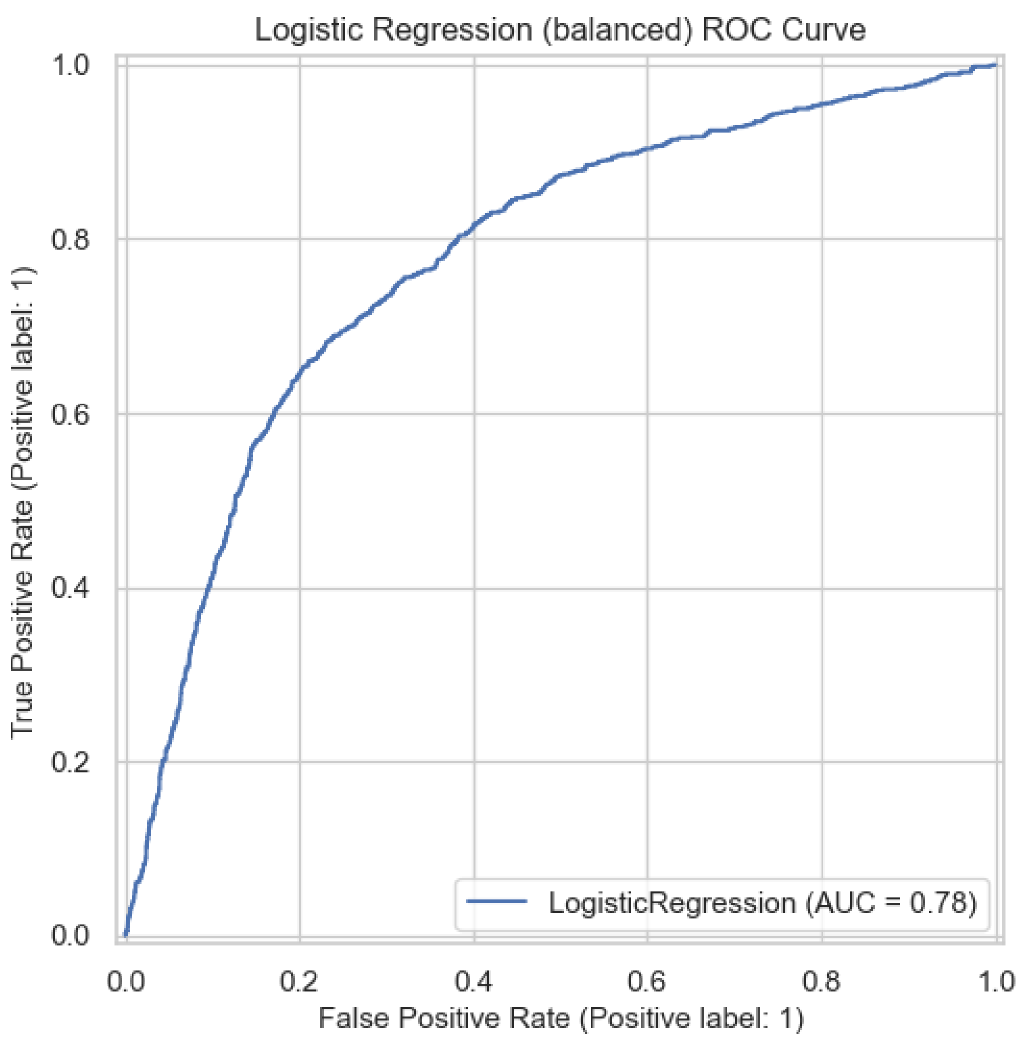
0.14 Section 12. Baseline supervised model

We train two logistic regression baselines on the processed features. We compare the standard model and the class-weighted variant for the imbalanced target. We print the metrics and draw the ROC curve for the balanced model.

[13]:
```
# Fit two logistic regression baselines and evaluate
models = {
    "LogisticRegression": LogisticRegression(
        solver="lbfgs", max_iter=4000, tol=1e-3, n_jobs=-1,␣
 ↪random_state=RANDOM_STATE
    ),
    "LogisticRegression (balanced)": LogisticRegression(
        solver="lbfgs", max_iter=4000, tol=1e-3, n_jobs=-1,␣
 ↪class_weight="balanced", random_state=RANDOM_STATE
    ),
}

metrics_rows = []
for name, clf in models.items():
    clf.fit(X_train_processed, y_train)
    y_pred = clf.predict(X_test_processed)
    y_prob = clf.predict_proba(X_test_processed)[:, 1]
    metrics_rows.append({
        "model": name,
        "accuracy":  accuracy_score(y_test, y_pred),
        "precision": precision_score(y_test, y_pred, zero_division=0),
        "recall":    recall_score(y_test, y_pred, zero_division=0),
        "f1":        f1_score(y_test, y_pred, zero_division=0),
        "roc_auc":   roc_auc_score(y_test, y_prob),
    })

metrics_df = pd.DataFrame(metrics_rows).set_index("model")
display(metrics_df)

balanced_model = models["LogisticRegression (balanced)"]
RocCurveDisplay.from_estimator(balanced_model, X_test_processed, y_test)
plt.title("Logistic Regression (balanced) ROC Curve")
plt.show()

standard_metrics = metrics_df.loc["LogisticRegression"]
balanced_metrics = metrics_df.loc["LogisticRegression (balanced)"]
```

```
display(Markdown(
    f"Balanced model: accuracy {balanced_metrics['accuracy']:.3f}, "
    f"precision {balanced_metrics['precision']:.3f}, "
    f"recall {balanced_metrics['recall']:.3f}, "
    f"ROC AUC {balanced_metrics['roc_auc']:.3f}. "
    "The class-weighted setting improves recall for the minority class while␣
↪keeping AUC stable."
))
```

```
                              accuracy  precision    recall        f1  \
model
LogisticRegression            0.777140   0.585160  0.363351  0.448320
LogisticRegression (balanced) 0.742693   0.488441  0.685864  0.570557

                               roc_auc
model
LogisticRegression            0.774860
LogisticRegression (balanced) 0.777076
```



Balanced model: accuracy 0.743, precision 0.488, recall 0.686, ROC AUC 0.777. The class-weighted setting improves recall for the minority class while keeping AUC stable.

0.15 Section 13. Summary and what improved

We summarize imputation, outlier illustration, feature dimensionality, and baseline model results from this run. Counts come from the fitted pipeline to avoid drift.

[14]:
```
from IPython.display import Markdown, display
import numpy as np
import pandas as pd
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, roc_auc_score

if isinstance(preprocessor, ColumnTransformer):
    column_mapper = preprocessor
elif isinstance(preprocessor, Pipeline) and "columns" in preprocessor.
↪named_steps:
    column_mapper = preprocessor.named_steps["columns"]
else:
    raise ValueError("Expected 'preprocessor' to be a ColumnTransformer or a␣
↪Pipeline with a 'columns' step.")

# Feature counts
raw_inputs_branch_total = 0
raw_inputs_unique_set = set()
for _, trans, cols in column_mapper.transformers:
    if trans == "drop" or cols == "drop":
        continue
    if isinstance(cols, (list, tuple, np.ndarray)):
        raw_inputs_branch_total += len(cols)
        raw_inputs_unique_set.update(cols)
    else:
        raw_inputs_branch_total += 1
        raw_inputs_unique_set.add(cols)

feature_count_before_encoding_unique = len(raw_inputs_unique_set)
feature_count_before_encoding = raw_inputs_branch_total

try:
    feature_names = column_mapper.get_feature_names_out()
    feature_count_after = len(feature_names)
except Exception:
```

```python
    Xt_one = column_mapper.transform(X_train.iloc[[0]])
    feature_count_after = Xt_one.shape[1]
    feature_names = None

# Outlier illustration total (EDA copy), safe fallback if the table is absent
if "total_outliers_capped" not in globals():
    try:
        total_outliers_capped = int(
            outlier_summary_df[["capped_below_demo", "capped_above_demo"]].
 ↪sum().sum()
        )
    except Exception:
        total_outliers_capped = 0

# Retrieve metrics from Section 12 or recompute from fitted models
def _ensure_log_reg_metrics():
    if "metrics_df" in globals():
        std_ok = "LogisticRegression" in metrics_df.index
        bal_ok = "LogisticRegression (balanced)" in metrics_df.index
        if std_ok and bal_ok:
            return metrics_df.loc["LogisticRegression"], metrics_df.
 ↪loc["LogisticRegression (balanced)"]

    std_model = None
    bal_model = None
    if "models" in globals():
        std_model = models.get("LogisticRegression")
        bal_model = models.get("LogisticRegression (balanced)")

    rows = {}
    if std_model is not None:
        y_pred = std_model.predict(X_test_processed)
        y_prob = std_model.predict_proba(X_test_processed)[:, 1]
        rows["LogisticRegression"] = {
            "accuracy":  accuracy_score(y_test, y_pred),
            "precision": precision_score(y_test, y_pred, zero_division=0),
            "recall":    recall_score(y_test, y_pred, zero_division=0),
            "f1":        f1_score(y_test, y_pred, zero_division=0),
            "roc_auc":   roc_auc_score(y_test, y_prob),
        }
    if bal_model is not None:
        y_pred = bal_model.predict(X_test_processed)
        y_prob = bal_model.predict_proba(X_test_processed)[:, 1]
        rows["LogisticRegression (balanced)"] = {
            "accuracy":  accuracy_score(y_test, y_pred),
            "precision": precision_score(y_test, y_pred, zero_division=0),
            "recall":    recall_score(y_test, y_pred, zero_division=0),
```

```
            "f1":        f1_score(y_test, y_pred, zero_division=0),
            "roc_auc":   roc_auc_score(y_test, y_prob),
        }

    if rows:
        mdf = pd.DataFrame(rows).T
        class _Row(dict):
            __getattr__ = dict.get
        std_row = _Row(mdf.loc["LogisticRegression"].to_dict()) if␣
↪"LogisticRegression" in mdf.index else None
        bal_row = _Row(mdf.loc["LogisticRegression (balanced)"].to_dict()) if␣
↪"LogisticRegression (balanced)" in mdf.index else None
        if std_row is not None and bal_row is not None:
            return std_row, bal_row

    raise RuntimeError("Could not locate logistic regression metrics from␣
↪Section 12.")

standard_metrics, balanced_metrics = _ensure_log_reg_metrics()

if "missing_before_total" not in globals():
    missing_before_total = int(df.isna().sum().sum())
if "missing_after_total" not in globals():
    try:
        modeled_cols = list(set(numeric_features) | set(categorical_features))
    except Exception:
        modeled_cols = df.columns.tolist()
    missing_after_total = int(df[modeled_cols].isna().sum().sum())

processing_md = f"""
### Data processing

**Missing values**: {missing_before_total} before imputation,␣
↪{missing_after_total} after
**Outliers (EDA illustration)**: {total_outliers_capped} values shown as capped;
↪ robust capping is applied in the train-only pipeline
**Feature dimensionality**: {feature_count_before_encoding_unique} unique raw␣
↪inputs ({feature_count_before_encoding} across branches) →␣
↪{feature_count_after} model features
"""

display(Markdown(processing_md))

metrics_table = pd.DataFrame(
    {
```

```
        "accuracy":  [standard_metrics["accuracy"], ␣
↪balanced_metrics["accuracy"]],
        "precision": [standard_metrics["precision"],␣
↪balanced_metrics["precision"]],
        "recall":    [standard_metrics["recall"],   ␣
↪balanced_metrics["recall"]],
        "f1":        [standard_metrics["f1"],        balanced_metrics["f1"]],
        "roc_auc":   [standard_metrics["roc_auc"],  ␣
↪balanced_metrics["roc_auc"]],
    },
    index=["LogisticRegression", "LogisticRegression (balanced)"],
)
display(metrics_table.round(3))

if "hgb" in globals():
    y_prob_hgb = hgb.predict_proba(X_test_processed)[:, 1]
    y_pred_hgb = (y_prob_hgb >= 0.5).astype(int)
    hgb_row = pd.DataFrame(
        {
            "accuracy":  [accuracy_score(y_test, y_pred_hgb)],
            "precision": [precision_score(y_test, y_pred_hgb, zero_division=0)],
            "recall":    [recall_score(y_test, y_pred_hgb, zero_division=0)],
            "f1":        [f1_score(y_test, y_pred_hgb, zero_division=0)],
            "roc_auc":   [roc_auc_score(y_test, y_prob_hgb)],
        },
        index=["HistGradientBoosting"],
    )
    display(hgb_row.round(3))
```

0.15.1 Data processing

Missing values: 20733 before imputation, 0 after
Outliers (EDA illustration): 984 values shown as capped; robust capping is applied in the train-only pipeline
Feature dimensionality: 15 unique raw inputs (16 across branches) → 133 model features

	accuracy	precision	recall	f1	roc_auc
LogisticRegression	0.777	0.585	0.363	0.448	0.775
LogisticRegression (balanced)	0.743	0.488	0.686	0.571	0.777