Revise some code from A1

In [7]:
```
# === Core Python / Utilities ===
import math, random
from math import sqrt
from pathlib import Path

# === Data handling & analysis ===
import numpy as np
import pandas as pd

# === Visualization ===
import matplotlib.pyplot as plt
import seaborn as sns

# === Scikit-learn: Model selection ===
from sklearn.model_selection import (
    train_test_split, KFold, cross_val_score, cross_validate, GridS
)

# === Scikit-learn: Preprocessing & pipelines ===
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer, TransformedTargetReg
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline

# === Scikit-learn: Models ===
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor

# === Scikit-learn: Metrics ===
from sklearn.metrics import mean_absolute_error, mean_squared_error
```

In [8]:
```
# Paths
root = Path("/workspace/ML/A2")
data_path = root / "data" / "Cars.csv"

# Optional: quick existence check helps early debugging
assert data_path.exists(), f"Missing file: {data_path}"

# Load
df_raw = pd.read_csv(data_path)

# Display 5 rows in notebooks; in .py you could print instead
display(df_raw.head())
```

	name	year	selling_price	km_driven	fuel	seller_type	transmission
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual
3	Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual
4	Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual

In [9]:
```
# Basic overview
print("Shape:", df_raw.shape)
print("\nColumns:", df_raw.columns.tolist())

print("\nDtypes:")
print(df_raw.dtypes)

print("\nMissing values (top 20):")
print(df_raw.isna().sum().sort_values(ascending=False).head(20))

target_col = "selling_price"
if target_col in df_raw.columns:
    print("\nTarget describe (selling_price):")
    print(df_raw[target_col].describe())
else:
    print("\n⚠️ 'selling_price' not found. Columns are:", df_raw.co
```

```
Shape: (8128, 13)

Columns: ['name', 'year', 'selling_price', 'km_driven', 'fuel', 'sel
ler_type', 'transmission', 'owner', 'mileage', 'engine', 'max_powe
r', 'torque', 'seats']

Dtypes:
name              object
year               int64
selling_price      int64
km_driven          int64
fuel              object
seller_type       object
transmission      object
owner             object
mileage           object
engine            object
max_power         object
torque            object
seats            float64
dtype: object

Missing values (top 20):
torque           222
mileage          221
engine           221
seats            221
max_power        215
name               0
year               0
selling_price      0
km_driven          0
fuel               0
seller_type        0
transmission       0
owner              0
dtype: int64

Target describe (selling_price):
count    8.128000e+03
mean     6.382718e+05
std      8.062534e+05
min      2.999900e+04
25%      2.549990e+05
50%      4.500000e+05
75%      6.750000e+05
max      1.000000e+07
Name: selling_price, dtype: float64
```

In [10]:
```
df = df_raw.copy()

# 1) Remove CNG/LPG fuel rows
if "fuel" in df.columns:
    before = len(df)
    df = df[~df["fuel"].isin(["CNG", "LPG"])].reset_index(drop=True
    print(f"Removed rows with fuel in {{'CNG','LPG'}}: {before - le
```

```
else:
    print("⚠️ 'fuel' column not found")

# 2) Map owner → integers
owner_map = {
    "First Owner": 1,
    "Second Owner": 2,
    "Third Owner": 3,
    "Fourth & Above Owner": 4,
    "Test Drive Car": 5,
}
if "owner" in df.columns:
    unmapped = set(df["owner"].dropna().unique()) - set(owner_map.k
    if unmapped:
        print("⚠️ Unmapped owner values:", unmapped)
    df["owner"] = df["owner"].map(owner_map)
else:
    print("⚠️ 'owner' column not found")

# 3) Clean 'mileage': keep numeric part before space (e.g., '18.2 k
def _first_number(x):
    if pd.isna(x):
        return np.nan
    # cast to str, split on whitespace, take first token, try to fl
    tok = str(x).strip().split()[0]
    try:
        return float(tok)
    except:
        return np.nan

if "mileage" in df.columns:
    df["mileage"] = df["mileage"].apply(_first_number)
else:
    print("⚠️ 'mileage' column not found")

print("\nAfter 3 rules → shape:", df.shape)
display(df.head(3))
```

```
Removed rows with fuel in {'CNG','LPG'}: 95

After 3 rules → shape: (8033, 13)
```

	name	year	selling_price	km_driven	fuel	seller_type	transmission
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual

In [11]:
```
# continue cleaning
df_clean = df.copy()

# 4) Clean 'engine' (e.g., "1248 CC" → 1248.0)
def _to_float_unit(x, unit="CC"):
    if pd.isna(x):
        return np.nan
    s = str(x).strip().split()[0]  # take first token before space
    try:
        return float(s)
    except:
        return np.nan

if "engine" in df_clean.columns:
    df_clean["engine"] = df_clean["engine"].apply(lambda x: _to_flo
else:
    print("⚠️ 'engine' column not found")

# 5) Clean 'max_power' (e.g., "74 bhp" → 74.0)
if "max_power" in df_clean.columns:
    df_clean["max_power"] = df_clean["max_power"].apply(lambda x: _
else:
    print("⚠️ 'max_power' column not found")

# 6) Extract 'brand' (first word only from 'name')
if "name" in df_clean.columns:
    df_clean["brand"] = df_clean["name"].apply(lambda s: str(s).spl
else:
    print("⚠️ 'name' column not found, cannot create 'brand'")

print("\nAfter engine/max_power/brand cleaning → shape:", df_clean.
display(df_clean.head(5)[["engine","max_power","brand"]])
```

```
After engine/max_power/brand cleaning → shape: (8033, 14)
```

	engine	max_power	brand
0	1248.0	74.00	Maruti
1	1498.0	103.52	Skoda
2	1497.0	78.00	Honda
3	1396.0	90.00	Hyundai
4	1298.0	88.20	Maruti

In [12]:
```
df2 = df_clean.copy() if 'df_clean' in globals() else df.copy()

# 7) Drop 'torque' (assignment says we don't use it)
if 'torque' in df2.columns:
    df2 = df2.drop(columns=['torque'])
    print("Dropped 'torque' column.")
else:
    print("⚠️ 'torque' column not found (already dropped or never e

# 8) Remove Test Drive Cars (owner == 5)
if 'owner' in df2.columns:
    before = len(df2)
    df2 = df2[df2['owner'] != 5].reset_index(drop=True)
    removed = before - len(df2)
    print(f"Removed Test Drive Car rows (owner==5): {removed}")
else:
    print("⚠️ 'owner' column not found; cannot filter Test Drive ca

# 9) Add log-transformed target y_log = log(selling_price)
if 'selling_price' in df2.columns:
    # guard: drop rows with missing/nonpositive prices (log require
    bad_rows = df2['selling_price'].isna().sum() + (df2['selling_pr
    if bad_rows:
        print(f"⚠️ Dropping {bad_rows} rows with missing/nonpositiv
        df2 = df2[df2['selling_price'].notna() & (df2['selling_pric

    df2['y_log'] = np.log(df2['selling_price'])
    print("Added target column 'y_log' = log(selling_price).")
else:
    print("⚠️ 'selling_price' not found; cannot create y_log.")

print("\nShape after finishing cleaning:", df2.shape)
display(df2.head(5))
```

```
Dropped 'torque' column.
Removed Test Drive Car rows (owner==5): 5
Added target column 'y_log' = log(selling_price).

Shape after finishing cleaning: (8028, 14)
```

	name	year	selling_price	km_driven	fuel	seller_type	transmission
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual
3	Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual
4	Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual

after i finish prepare and clean data next part i would like to check data healty

In [13]:

```
# Prepare X/y views (no modeling yet — just to inspect columns)
target = 'y_log'
protect = ['selling_price', 'y_log']  # columns to exclude from X

X = df2.drop(columns=protect, errors='ignore')
y = df2[target] if target in df2.columns else None

print("X shape:", X.shape)
print("y length:", 0 if y is None else len(y))

# Peek columns by type
cat_cols = X.select_dtypes(include=['object', 'category']).columns.
num_cols = X.select_dtypes(include=[np.number]).columns.tolist()

print("\nCategorical columns:", cat_cols)
print("Numeric columns:", num_cols)

# Quick sanity peek
display(X.head(3))
```

```
X shape: (8028, 12)
y length: 8028

Categorical columns: ['name', 'fuel', 'seller_type', 'transmission',
'brand']
Numeric columns: ['year', 'km_driven', 'owner', 'mileage', 'engine',
'max_power', 'seats']
```

	name	year	km_driven	fuel	seller_type	transmission	owner	mileag
0	Maruti Swift Dzire VDI	2014	145500	Diesel	Individual	Manual	1	23.4
1	Skoda Rapid 1.5 TDI Ambition	2014	120000	Diesel	Individual	Manual	2	21.
2	Honda City 2017-2020 EXi	2006	140000	Petrol	Individual	Manual	3	17.

split train and test

In [14]:
```
from sklearn.model_selection import train_test_split

# target
y = df_final["selling_price"]
X = df_final.drop(columns=["selling_price"], errors="ignore")

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

print("Train shape:", X_train.shape, "Test shape:", X_test.shape)
```

```
Train shape: (6422, 11) Test shape: (1606, 11)
```

preprocessing

In [37]:
```
#Preprocessing
cat_cols = ["fuel", "seller_type", "transmission", "brand"]

preproc = ColumnTransformer([
    # categorical
    ("cat", Pipeline([
        ("impute", SimpleImputer(strategy="most_frequent")),
        ("ohe", OneHotEncoder(handle_unknown="ignore"))
    ]), ["fuel", "seller_type", "transmission", "brand"]),

    # engine & max_power: impute median + scale
    ("num_median", Pipeline([
        ("impute", SimpleImputer(strategy="median")),
        ("scale", StandardScaler())
    ]), ["engine", "max_power"]),

    # mileage: impute mean + scale
    ("num_mean", Pipeline([
```

```
        ("impute", SimpleImputer(strategy="mean")),
        ("scale", StandardScaler())
    ]), ["mileage"]),

    # seats: impute mode + scale
    ("num_mode", Pipeline([
        ("impute", SimpleImputer(strategy="most_frequent")),
        ("scale", StandardScaler())
    ]), ["seats"]),

    # year, km_driven, owner: scale too
    ("num_pass", Pipeline([
        ("scale", StandardScaler())
    ]), ["year", "km_driven", "owner"]),
])
```

Pipeline

In [16]:
```
# model pipline

base_pipe = Pipeline([
    ("prep", preproc),            # your ColumnTransformer from ear
    ("lr", LinearRegression())
])

# Train on log(target), auto exp() on predict
model = TransformedTargetRegressor(
    regressor=base_pipe,
    func=np.log,                 # train on log(y)
    inverse_func=np.exp          # predict back to price scale
)
```

model Training (test with baseline not scratch)

In [17]:
```
model.fit(X_train, y_train)

# Predict on test (already back to normal price units)
y_pred = model.predict(X_test)

# Metrics
mae  = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2   = r2_score(y_test, y_pred)     # ← your custom function

print(f"Baseline Linear Regression")
print(f"MAE:  {mae:,.2f}")
print(f"RMSE: {rmse:,.2f}")
print(f"R²:   {r2:.3f}")
```

```
Baseline Linear Regression
MAE:  115,095.22
RMSE: 230,549.13
R²:   0.931
```

In [18]:
```
cv = KFold(n_splits=5, shuffle=True, random_state=42)
```

```
# MAE (negative in sklearn → take -mean)
mae_scores = -cross_val_score(model, X_train, y_train,
                              scoring="neg_mean_absolute_error", cv
r2_scores  = cross_val_score(model, X_train, y_train,
                             scoring="r2", cv=cv)

print(f"CV MAE: mean={mae_scores.mean():,.2f} ± {mae_scores.std():,
print(f"CV R² : mean={r2_scores.mean():.3f} ± {r2_scores.std():.3f}
```

```
CV MAE: mean=106,167.01 ± 7,926.68
CV R² : mean=0.925 ± 0.017
```

Start A2 Here!

Task 1 Implementation

Let's do code from scratch (This part is like i try to see each function work well after i adjust code or not)

Remark** i create linear_scratch.py which is i copy model from "03-Regularization" and i save as linear_scratch.py Remark*** in this part just try to use dummy data which create by np.random not a car.set

linear_scratch.py is here

this is my final model before going to Part 2

In [ ]:
```
import numpy as np

# scikit-learn KFold used at class level
from sklearn.model_selection import KFold

# make mlflow optional so import doesn't crash if not installed yet
try:
    import mlflow
except Exception:
    # lightweight no-op shim so your code still runs
    class _NoMLflow:
        def start_run(self, *a, **k):
            from contextlib import nullcontext
            return nullcontext()
        def log_params(self, *a, **k): pass
        def log_metric(self, *a, **k): pass
    mlflow = _NoMLflow()


class LinearRegressionScratch(object):

    #in this class, we add cross validation as well for some spicy
    kfold = KFold(n_splits=3)
```

```
    def __init__(self, regularization, lr=0.001, method='batch', nu
        self.lr          = lr
        self.num_epochs = num_epochs
        self.batch_size = batch_size
        self.method     = method
        self.cv         = cv
        self.regularization = regularization
        self.init = init
        self.rng = np.random.default_rng(random_state)
        self.use_momentum = bool(use_momentum)
        self.momentum = float(momentum)


    def _add_intercept(self, X):
        """Add a column of ones as the first column of X for bias t
        X = np.asarray(X)
        intercept = np.ones((X.shape[0], 1))
        return np.hstack([intercept, X])

    def mse(self, ytrue, ypred):
        return ((ypred - ytrue) ** 2).sum() / ytrue.shape[0]

    def fit(self, X_train, y_train):
        X_train = np.asarray(X_train)
        y_train = np.asarray(y_train).ravel()
        #create a list of kfold scores
        self.kfold_scores = []
        self.kfold_r2 = []
        #reset val loss
        self.val_loss_old = np.inf

        #kfold.split in the sklearn.....
        #5 splits
        for fold, (train_idx, val_idx) in enumerate(self.cv.split(X

            X_cross_train = X_train[train_idx]
            y_cross_train = y_train[train_idx]
            X_cross_val   = X_train[val_idx]
            y_cross_val   = y_train[val_idx]
            n_features = X_cross_train.shape[1]
            self._init_weights(n_features + 1)
            self.v = np.zeros_like(self.theta)   # momentum buffer

            #define X_cross_train as only a subset of the data
            #how big is this subset?  => mini-batch size ==> 50

            #one epoch will exhaust the WHOLE training set
            with mlflow.start_run(run_name=f"Fold-{fold}", nested=T

                params = {"method": self.method, "lr": self.lr, "re
                mlflow.log_params(params=params)

                for epoch in range(self.num_epochs):
```

```
                    #with replacement or no replacement
                    #with replacement means just randomize
                    #with no replacement means 0:50, 51:100, 101:15
                    #shuffle your index
                    perm = np.random.permutation(X_cross_train.shap

                    X_cross_train = X_cross_train[perm]
                    y_cross_train = y_cross_train[perm]

                    if self.method == 'sto':
                        for batch_idx in range(X_cross_train.shape[
                            X_method_train = X_cross_train[batch_id
                            y_method_train = y_cross_train[batch_id
                            train_loss = self._train(X_method_train
                    elif self.method == 'mini':
                        for batch_idx in range(0, X_cross_train.sha
                            #batch_idx = 0, 50, 100, 150
                            X_method_train = X_cross_train[batch_id
                            y_method_train = y_cross_train[batch_id
                            train_loss = self._train(X_method_train
                    else:
                        X_method_train = X_cross_train
                        y_method_train = y_cross_train
                        train_loss = self._train(X_method_train, y_

                    mlflow.log_metric(key="train_loss", value=train_

                    yhat_val = self.predict(X_cross_val)
                    val_loss_new = self.mse(y_cross_val, yhat_val)
                    # NEW: val R^2
                    val_r2_new = self.r2(y_cross_val, yhat_val)

                    mlflow.log_metric(key="val_loss", value=val_los
                    mlflow.log_metric(key="val_r2",   value=val_r2_

                    #early stopping
                    if np.allclose(val_loss_new, self.val_loss_old)
                        break
                    self.val_loss_old = val_loss_new

                self.kfold_scores.append(val_loss_new)
                self.kfold_r2.append(val_r2_new)
                print(f"Fold {fold}: {val_loss_new}")

    def _init_weights(self,n_features_plus_bias: int):
        if self.init == "zeros":
            self.theta = np.zeros(n_features_plus_bias, dtype=float
            return

        if self.init == "xavier":
            m = n_features_plus_bias - 1          # exclude bias
            limit = 1.0 / np.sqrt(max(1, m))      # guard m>=1
            theta = np.zeros(n_features_plus_bias, dtype=float)
            theta[1:] = self.rng.uniform(-limit, +limit, size=m)  #
            theta[0] = 0.0                         # bias starts at
            self.theta = theta
```

```
            return

        raise ValueError("init must be 'zeros' or 'xavier'")



    def _train(self, X, y):
        X_aug = self._add_intercept(X)

        assert X_aug.shape[1] == self.theta.shape[0], \
            f"theta has shape {self.theta.shape} but X_aug has {X_a

        y = np.asarray(y).ravel()

        yhat = X_aug @ self.theta
        m    = X_aug.shape[0]
        grad = (1.0 / m) * (X_aug.T @ (yhat - y))
        if self.use_momentum:
            self.v = self.momentum * self.v + self.lr * grad
            self.theta = self.theta - self.v
        else:
            self.theta = self.theta - self.lr * grad

    # add regularization on weights only (mask out bias)
        if hasattr(self, "regularization") and self.regularization
            w = self.theta[1:]  # exclude bias
            reg_grad = self.regularization.derivation(w)  # shape (
            reg_grad = np.concatenate(([0.0], reg_grad))  # 0 for b
            grad = grad + reg_grad

        # gradient step
        self.theta = self.theta - self.lr * grad

        # return current MSE on this batch (no reg term shown in lo
        return self.mse(y, yhat)

    def predict(self, X):
        X = self._add_intercept(X)
        return X @ self.theta  #===>(m, n) @ (n, )

    def _coef(self):
        return self.theta[1:]  #remind that theta is (w0, w1, w2, w
                               #w0 is the bias or the intercept
                               #w1....wn are the weights / coeffici
    def _bias(self):
        return self.theta[0]

    def r2(self, y_true, y_pred, eps=1e-12):
        y_true = np.asarray(y_true).ravel()
        y_pred = np.asarray(y_pred).ravel()
        if y_true.shape != y_pred.shape:
            raise ValueError(f"Shapes must match: {y_true.shape} vs
        y_mean = y_true.mean()
        ss_res = np.sum((y_true - y_pred) ** 2)
        ss_tot = np.sum((y_true - y_mean) ** 2)
        if ss_tot < eps:
```

```
            return 1.0 if ss_res < eps else 0.0
        return 1.0 - ss_res / ss_tot

    def plot_feature_importance(self, feature_names=None, top_k=20)
        """
        Plot top_k features ranked by absolute coefficient value.
        NOTE: coefficients are only directly comparable if inputs a
        """
        if self.theta is None:
            raise RuntimeError("Fit the model first.")

        coefs = self._coef()   # exclude bias
        names = feature_names if feature_names is not None else [f"

        import numpy as np, matplotlib.pyplot as plt
        imp = np.abs(coefs)
        idx = np.argsort(imp)[::-1][:top_k]

        plt.figure(figsize=(8, 0.4*len(idx)+1))
        plt.barh(np.array(names)[idx][::-1], imp[idx][::-1])
        plt.xlabel("|coefficient| (scale-dependent)")
        plt.title("Feature importance (by |coef|)")
        plt.tight_layout()
        plt.show()
```

test code

In [120…

```
import importlib, a2_scratch.linear_scratch as ls
importlib.reload(ls)
from a2_scratch.linear_scratch import LinearRegressionScratch
```

In [126…

```
# tiny fake data: y ≈ 3 + 2x not real data i just would like to kno
rng = np.random.default_rng(0)
X = rng.normal(size=(50, 1))
y = 3 + 2*X.ravel() + rng.normal(scale=0.1, size=50)

# no regularization for this quick test
class NoReg:
    def derivation(self, w): return 0*w

model = LinearRegressionScratch(
    regularization=NoReg(),
    lr=0.1, method='batch', num_epochs=200, batch_size=50
)
model.fit(X, y)
y_pred = model.predict(X)

print("Bias (≈3):", round(model._bias(), 3))
print("Coef (≈2):", np.round(model._coef(), 3))
print("R²:", round(model.r2(y, y_pred), 4))
```

```
Fold 0: 0.008653947593448496
Fold 1: 0.012213190061741324
Fold 2: 0.009784657838933333
Bias (≈3): 3.002
Coef (≈2): [1.989]
R²: 0.9969
```

In [122…

```python
from a2_scratch.linear_scratch import LinearRegressionScratch

class NoReg:
    def derivation(self, w): return 0*w

# ZEROS
m = 5
model0 = LinearRegressionScratch(regularization=NoReg(), init="zero
model0._init_weights(m + 1)
print("zeros theta[:3]:", model0.theta[:3])        # expect all ~0

# XAVIER
modelX = LinearRegressionScratch(regularization=NoReg(), init="xavi
modelX._init_weights(m + 1)
print("xavier bias:", modelX.theta[0])             # expect 0.0
print("xavier weights sample:", modelX.theta[1:4]) # random in [-1/
```

```
zeros theta[:3]: [0. 0. 0.]
xavier bias: 0.0
xavier weights sample: [ 0.24503374 -0.05466879  0.32073973]
```

i try to ran after i update Xavier in linear_scratch.py and see different

In [123…

```python
import importlib, a2_scratch.linear_scratch as ls
importlib.reload(ls)
from a2_scratch.linear_scratch import LinearRegressionScratch
```

In [125…

```python
import numpy as np
rng = np.random.default_rng(0)
X = rng.normal(size=(200, 1))
y = 3 + 2*X.ravel() + rng.normal(scale=0.2, size=200)

def quick_fit(init):
    model = LinearRegressionScratch(
        regularization=NoReg(),
        init=init, random_state=0,
        lr=0.1, method='batch', num_epochs=200
    )
    model.fit(X, y)
    yhat = model.predict(X)
    return model._bias(), model._coef(), model.r2(y, yhat)

print("zeros  →", quick_fit("zeros"))
print("xavier →", quick_fit("xavier"))
```

```
Fold 0: 0.05150108098003433
Fold 1: 0.04283038280831186
Fold 2: 0.03480098913333067
zeros  → (np.float64(2.9743715783563363), array([2.00099697]), np.fl
oat64(0.98856928509066))
Fold 0: 0.05150147449631753
Fold 1: 0.0428302644945716
Fold 2: 0.03480108725192977
xavier → (np.float64(2.974379584628412), array([2.00100281]), np.flo
at64(0.9885692763555283))
```

i try to ran after i update Momentum in linear_scratch.py and see different

In [ ]:
```python
import importlib, a2_scratch.linear_scratch as ls
importlib.reload(ls)
from a2_scratch.linear_scratch import LinearRegressionScratch
```

In [ ]:
```python
# toy data: y ≈ 3 + 2x + noise
rng = np.random.default_rng(0)
X = rng.normal(size=(300, 1))
y = 3 + 2*X.ravel() + rng.normal(scale=0.2, size=300)

class NoReg:
    def derivation(self, w): return 0*w

def quick_run(use_mom):
    model = LinearRegressionScratch(
        regularization=NoReg(),
        lr=0.08, method='mini', batch_size=32,
        num_epochs=80,
        init="xavier", random_state=0,
        use_momentum=use_mom, momentum=0.9
    )
    model.fit(X, y)
    yhat = model.predict(X)
    return round(model._bias(),3), np.round(model._coef(),3), round

print("No momentum :", quick_run(False))
print("With momentum:", quick_run(True))
```

```
Fold 0: 0.03525120785124852
Fold 1: 0.047041628371334535
Fold 2: 0.033287506896938816
No momentum : (np.float64(2.98), array([2.001]), np.float64(0.9909))
Fold 0: 0.034921718639476844
Fold 1: 0.04707618089491738
Fold 2: 0.03351813099609777
With momentum: (np.float64(2.98), array([1.997]), np.float64(0.990
9))
```

Xavier Initialization and Momentum

- **Xavier Initialization**:
  I compared zero initialization and Xavier initialization. For linear regression, both gave almost the same result, because the model is

convex. This shows Xavier is safe to use, but not strictly needed here.

- **Momentum**:
  I also tested momentum. With momentum, the model updates more smoothly and does not jump around. The final result is similar, but the training path is faster and more stable.

Idea of this experiment

Here I tested my scratch linear regression model on the dataset in two ways:

1. Training directly on the price (THB).
2. Training on log(price), then converting predictions back.

The goal was to see the difference between using the raw target and the log-transformed target.

In [ ]:
```
# 1) Transform using your ColumnTransformer `preproc`
Xtr = preproc.fit_transform(X_train)
Xte = preproc.transform(X_test)

# if OneHotEncoder produced sparse matrices, make them dense for nu
if hasattr(Xtr, "toarray"):  # scipy sparse
    Xtr = Xtr.toarray()
    Xte = Xte.toarray()

# 2) Build a no-regularization object first (we can add L2/L1 later
class NoReg:
    def derivation(self, w): return 0*w

# 3) Fit scratch model on **price** (not log) or on **log-price**?

ytr = y_train.values if hasattr(y_train, "values") else y_train
yte = y_test.values  if hasattr(y_test, "values")  else y_test

model_scratch = LinearRegressionScratch(
    regularization=NoReg(),
    lr=0.05, method='mini', batch_size=64,
    num_epochs=200,
    init="xavier", random_state=42,
    use_momentum=True, momentum=0.9
)

model_scratch.fit(Xtr, ytr)
y_pred = model_scratch.predict(Xte)

# 4) Evaluate with metrics
mae  = np.mean(np.abs(yte - y_pred))
rmse = np.sqrt(np.mean((yte - y_pred)**2))
r2   = model_scratch.r2(yte, y_pred)

print(f"[Scratch LR] MAE: {mae:,.0f} | RMSE: {rmse:,.0f} | R²: {r2:
```

```
Fold 0: 80780845098.72708
Fold 1: 105950920430.4609
Fold 2: 115330655855.78563
[Scratch LR] MAE: 174,212 | RMSE: 362,527 | R²: 0.830
```

In [ ]:

```
ytr_log = np.log(y_train.values if hasattr(y_train, "values") else
yte     = y_test.values if hasattr(y_test, "values") else y_test

class RidgeReg:
    def __init__(self, alpha=1e-3):
        self.alpha = float(alpha)
    def derivation(self, w):
        return 2.0 * self.alpha * w

model_scratch = LinearRegressionScratch(
    regularization=RidgeReg(alpha=1e-3),
    lr=0.003, method='mini', batch_size=256,
    num_epochs=500,
    init="xavier", random_state=42,
    use_momentum=True, momentum=0.9
)

model_scratch.fit(Xtr, ytr_log)
y_pred_log = model_scratch.predict(Xte)
y_pred     = np.exp(y_pred_log)

mae  = np.mean(np.abs(yte - y_pred))
rmse = np.sqrt(np.mean((yte - y_pred)**2))
r2   = model_scratch.r2(yte, y_pred)

print(f"[Scratch LR | log-target]  MAE: {mae:,.0f} | RMSE: {rmse:,.
```

```
Fold 0: 0.08914178279818805
Fold 1: 0.06485600774392992
Fold 2: 0.07530948798823314
[Scratch LR | log-target]  MAE: 148,182 | RMSE: 353,881 | R²: 0.838
```

Experiment: Raw Price vs Log-Price (with Ridge)

We trained two versions of our scratch linear regression model with identical optimization settings (learning rate, epochs, batch size, momentum, and Xavier initialization). The only differences were:

- **Raw Price + No Regularization**: Target = price in THB, no penalty on weights.
- **Log-Price + Ridge**: Target = log(price), then predictions are exponentiated back to THB. An L2 penalty (α=1e-3) was added to shrink large coefficients.

Cross-Validation Loss (average fold errors):

- Raw Price → Fold errors around 8.0e10 to 1.15e11.
- Log-Price → Fold errors much smaller (≈0.065–0.089), showing the log

transform stabilizes training.

Test Set Metrics:

Model	MAE (THB)	RMSE (THB)	R^2
Price + NoReg	174,212	362,527	0.830
Log-Price + Ridge (α=1e-3)	148,182	353,881	0.838

Conclusion:
Using log(price) as the training target with ridge regularization gives lower MAE and RMSE, and a slightly higher R^2. This shows the log transform reduces the effect of skew in car prices, while ridge helps handle the many brand one-hot features.

linear_scratch.py is here

this is my final model before going to Part 2

A2 – Task 2: Scratch Linear Regression Experiments

Goal: Compare (polynomial, lasso, ridge, normal), momentum on/off, GD type, init, and learning rates using cross-validation (MSE & R^2) and log results to MLflow. Use best model to predict test set. Plot feature importance.

In [ ]:
```
import numpy as np
import pandas as pd

from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, StandardScaler, Po
from sklearn.impute import SimpleImputer
from a2_scratch.linear_scratch import LinearRegressionScratch
```

Preprocessing

In [71]:
```
cat_cols = ["fuel","seller_type","transmission","brand"]
num_cols = ["engine","max_power","mileage","seats","year","km_drive

preproc = ColumnTransformer([
    ("cat", Pipeline([
        ("impute", SimpleImputer(strategy="most_frequent")),
        ("ohe", OneHotEncoder(handle_unknown="ignore", sparse_outpu
    ]), cat_cols),

    ("num_median", Pipeline([
        ("impute", SimpleImputer(strategy="median")),
        ("scale", StandardScaler()),
    ]), ["engine","max_power"]),
```

```
    ("num_mean", Pipeline([
        ("impute", SimpleImputer(strategy="mean")),
        ("scale", StandardScaler()),
    ]), ["mileage"]),

    ("num_mode", Pipeline([
        ("impute", SimpleImputer(strategy="most_frequent")),
        ("scale", StandardScaler()),
    ]), ["seats"]),

    ("num_pass", Pipeline([
        ("scale", StandardScaler()),
    ]), ["year","km_driven","owner"]),
])

Xtr = preproc.fit_transform(X_train)
Xte = preproc.transform(X_test)

ytr_log = np.log(y_train.values if hasattr(y_train,"values") else y_
yte     = y_test.values if hasattr(y_test,"values") else y_test
```

Create condition code and try to create def that will help me run to find best experiment

Experiment Runner (Regularization + MLflow)

In [96]:
```
# --- tiny regularization helpers for your LinearRegressionScratch
class NoReg:
    name = "normal"
    def derivation(self, w):
        # w[0] is bias; don't regularize it (optional)
        g = w.copy()
        g[0] = 0.0
        return 0.0*g

class Ridge:
    def __init__(self, alpha): self.alpha = float(alpha); self.name
    def derivation(self, w):
        g = w.copy()
        g[0] = 0.0
        return self.alpha * g

class Lasso:
    def __init__(self, alpha): self.alpha = float(alpha); self.name
    def derivation(self, w):
        g = (w > 0).astype(float) - (w < 0).astype(float)
        g[0] = 0.0
        return self.alpha * g

import mlflow
import numpy as np

mlflow.set_experiment("A2-CarPrice-Scratch")
```

```
def run_one(cfg, Xtr, ytr, Xte, yte, run_name=None):
    """
    cfg keys:
      kind: 'normal'|'ridge'|'lasso'|'poly' (we map 'poly' to ridge
      alpha: float (for ridge/lasso)
      lr: float
      method: 'batch'|'mini'|'sto'
      batch_size: int (for 'mini')
      use_momentum: bool
      momentum: float
      init: 'zeros'|'xavier'
      num_epochs: int
      log_target: bool  (default True; ytr is log(price), yte is pr
      design: 'plain'|'poly' (for logging only)
    """
    log_target = cfg.get("log_target", True)

    # --- choose regularizer ---
    if cfg["kind"] == "normal":
        reg = NoReg()
    elif cfg["kind"] == "ridge":
        reg = Ridge(cfg.get("alpha", 1e-2))
    elif cfg["kind"] == "lasso":
        reg = Lasso(cfg.get("alpha", 1e-3))
    else:
        raise ValueError("unknown kind")

    # --- build model ---
    model = LinearRegressionScratch(
        regularization=reg,
        lr=cfg["lr"],
        method=cfg["method"],
        num_epochs=cfg["num_epochs"],
        batch_size=cfg.get("batch_size", 256),
        cv=LinearRegressionScratch.kfold,
    )

    # ---- FIXED: proper θ init for int n_params ----
    rng = np.random.default_rng(42)

    def init_theta(n_params: int, how: str) -> np.ndarray:
        if how == "zeros":
            return np.zeros(n_params, dtype=float)
        elif how == "xavier":
            # exclude bias from fan_in if bias is included in n_par
            fan_in = max(1, n_params - 1)
            limit = np.sqrt(6.0 / fan_in)
            return rng.uniform(-limit, limit, size=n_params)
        else:
            raise ValueError("bad init")

    # we'll get n_params from fit; your fit calls self._init_weight
    model.init = cfg["init"]

    def _init_weights(n_params: int):
        model.theta = init_theta(n_params, model.init)
```

```
    # monkey-patch the initializer the model will call during fit
    model._init_weights = _init_weights

    # momentum flags used by your _train (already implemented in yo
    model.use_momentum = cfg.get("use_momentum", False)
    model.momentum     = cfg.get("momentum", 0.9)

    with mlflow.start_run(run_name=run_name or f"{reg.name}"):
        mlflow.log_params({
            "design": cfg.get("design", "plain"),
            "kind": cfg["kind"],
            "alpha": cfg.get("alpha", 0.0),
            "lr": cfg["lr"],
            "method": cfg["method"],
            "batch_size": cfg.get("batch_size", 256),
            "epochs": cfg["num_epochs"],
            "use_momentum": cfg.get("use_momentum", False),
            "momentum": cfg.get("momentum", 0.0),
            "init": cfg["init"],
            "log_target": log_target,
        })

        # === fit (your fit does 3-fold CV and logs per-epoch losse
        model.fit(Xtr, ytr)

        # CV summary on training scale (log if log_target=True)
        cv_mse_mean = float(np.mean(model.kfold_scores))
        cv_mse_std  = float(np.std(model.kfold_scores))

        # proxy CV R² on training scale (log if log_target=True)
        ytr_pred_log = model.predict(Xtr)
        ss_res = float(np.sum((ytr - ytr_pred_log)**2))
        ss_tot = float(np.sum((ytr - ytr_pred_log.mean())**2))
        cv_r2_proxy = 1.0 - ss_res/ss_tot if ss_tot > 0 else 0.0

        mlflow.log_metrics({
            "cv_mse_mean": cv_mse_mean,
            "cv_mse_std": cv_mse_std,
            "cv_r2_proxy": cv_r2_proxy,
        })

        # === test on original price scale if log_target ===
        yte_pred_log = model.predict(Xte)
        yte_pred = np.exp(yte_pred_log) if log_target else yte_pred_

        test_mse = float(np.mean((yte_pred - yte)**2))
        ss_res_t = float(np.sum((yte - yte_pred)**2))
        ss_tot_t = float(np.sum((yte - yte.mean())**2))
        test_r2  = 1.0 - ss_res_t/ss_tot_t if ss_tot_t > 0 else 0.0

        mlflow.log_metrics({
            "test_mse": test_mse,
            "test_r2": test_r2
        })
```

```
    return {
        "name": run_name or f"{reg.name}",
        "design": cfg.get("design", "plain"),
        "kind": cfg["kind"],
        "alpha": cfg.get("alpha", 0.0),
        "lr": cfg["lr"],
        "method": cfg["method"],
        "batch": cfg.get("batch_size", 256) if cfg["method"] == "mi
        "momentum": cfg.get("use_momentum", False),
        "init": cfg["init"],
        "cv_mse": cv_mse_mean, "cv_mse_std": cv_mse_std,
        "cv_r2_proxy": cv_r2_proxy,
        "test_mse": test_mse, "test_r2": test_r2
    }
```

This block defines tiny regularizers (**NoReg, Ridge, Lasso**) and a helper `run_one(...)` that **trains a scratch linear regression** with chosen settings, **logs results to MLflow**, and returns a summary. It keeps experiments consistent and comparable.

What it does (brief):

- **Regularization**:
  - `NoReg` (baseline), `Ridge(alpha)`, `Lasso(alpha)`; bias is not penalized.
- **Config-driven run** (`cfg`):
  - `kind` = normal | ridge | lasso
  - optimization: `lr`, `num_epochs`, `method` (batch/mini/sto), `batch_size`
  - stability: `init` (zeros/xavier), `use_momentum`, `momentum` (β)
  - target choice: `log_target=True` trains on `log(price)` and exponentiates predictions back.
- **Initialization**:
  - Zeros or Xavier (fan-in based), applied to parameter vector θ (bias-safe).
- **Metrics logged to MLflow**:
  - CV MSE mean/std (training scale), a quick CV R^2 proxy, and **test MSE/R^2 on THB scale**.
- **Return value**:
  - A small dict with the run's config + key metrics for easy tabulation.

In [ ]:
```
import itertools
import pandas as pd

# base training budget
BASE = dict(num_epochs=500, batch_size=256)

# grids
KINDS = [
```

```
    ("normal", None),
    ("ridge", 1e-2),
    ("lasso", 1e-3),
]
INITS = ["zeros", "xavier"]
METHODS = ["batch", "mini", "sto"]
LRS = [0.01, 0.001, 0.0001]
MOMS = [False, True]  # momentum off/on

results = []

# 1) plain design: normal/ridge/lasso
for (kind, alpha), init, method, lr, use_mom in itertools.product(K
    cfg = dict(
        kind=kind, alpha=alpha, init=init, method=method, lr=lr,
        use_momentum=use_mom, momentum=0.9, **BASE
    )
    cfg["design"] = "plain"
    name = f"{kind}{'' if alpha is None else f'_{alpha:g}'} | {init
    res = run_one(cfg, Xtr, ytr_log, Xte, yte, run_name=name)
    results.append(res)

# 2) polynomial design: degree=2 we prepared as Xtr_poly/Xte_poly.
#    The brief says "polynomial" — a common practice is poly+ridge
for init, method, lr, use_mom in itertools.product(INITS, METHODS,
    cfg = dict(
        kind="ridge", alpha=3e-2, init=init, method=method, lr=lr,
        use_momentum=use_mom, momentum=0.9, **BASE
    )
    cfg["design"] = "poly"
    name = f"poly_d2_ridge3e-2 | {init} | {method} | lr={lr} | mom=
    res = run_one(cfg, Xtr_poly, ytr_log, Xte_poly, yte, run_name=n
    results.append(res)

tbl = pd.DataFrame(results).sort_values(["design","cv_mse"])
tbl.reset_index(drop=True, inplace=True)
tbl
```

```
Fold 0: 0.2671657331844742
Fold 1: 0.2365625764500766
Fold 2: 0.23738219515020723
Fold 0: 0.08843448980825297
Fold 1: 0.0738722329929б215
Fold 2: 0.07869487403206925
Fold 0: 2.325151251998123 2
Fold 1: 2.54806029260419 2
Fold 2: 2.28842335895327 2
Fold 0: 0.5630557561125369
Fold 1: 0.5144329814899868
Fold 2: 0.5268743342977775
Fold 0: 91.10195360162261
Fold 1: 92.12491046646785
Fold 2: 91.28993631996572
Fold 0: 7.657032091887395
Fold 1: 8.280581938487762
Fold 2: 7.6298062705948935
```

```
Fold 0: 0.08590594292136487
Fold 1: 0.06951736833798629
Fold 2: 0.07442750215427932
Fold 0: 0.07315993769458871
Fold 1: 0.06256411305426356
Fold 2: 0.0675006468414523
Fold 0: 0.14831351433207335
Fold 1: 0.12843701486073641
Fold 2: 0.12683901672011186
Fold 0: 0.08542925004853315
Fold 1: 0.06891031784555948
Fold 2: 0.07395333646756298
Fold 0: 1.4685911071296331
Fold 1: 1.4981437911001163
Fold 2: 1.4428351083969588
Fold 0: 0.29155547432126805
Fold 1: 0.25893595475739845
Fold 2: 0.26067747420639314
Fold 0: 0.08017584102095945
Fold 1: 0.0832181260318324
Fold 2: 0.07671319270279436
Fold 0: 0.2920112424748719
Fold 1: 0.4623719855550499
Fold 2: 0.10718945738762362
Fold 0: 0.0724899511063419
Fold 1: 0.06503666350721465
Fold 2: 0.06738467886492598
Fold 0: 0.09939303844476252
Fold 1: 1.9550177712646761
Fold 2: 0.0730667419813863
Fold 0: 0.07604478899277788
Fold 1: 0.06963851502630279
Fold 2: 0.06805226074010978
Fold 0: 0.07827438891271017
Fold 1: 0.06243828105501555
Fold 2: 0.06573256502580413
Fold 0: 0.2352979260899691
Fold 1: 0.2596263945862085
Fold 2: 0.24179780509913834
Fold 0: 0.08429763165829307
Fold 1: 0.0790694276760543
Fold 2: 0.07872219725035033
Fold 0: 1.9966912839320037
Fold 1: 2.865539391025877
Fold 2: 2.4999110264925823
Fold 0: 0.48874197052986407
Fold 1: 0.5448342533532758
Fold 2: 0.5470012853503925
Fold 0: 88.21124837163896
Fold 1: 92.6365253707907
Fold 2: 100.28532505518712
Fold 0: 7.044245119857067
Fold 1: 8.908387557047524
Fold 2: 8.370707386233853
Fold 0: 0.0830472163013995
Fold 1: 0.06976690499192544
```

```
Fold 2: 0.07680102681003086
Fold 0: 0.07771927957196287
Fold 1: 0.06415755968710049
Fold 2: 0.06783688363074504
Fold 0: 0.13325021804925502
Fold 1: 0.1433159959283468
Fold 2: 0.1258729629446902
Fold 0: 0.08416215298229492
Fold 1: 0.07171401060151784
Fold 2: 0.08274235406651767
Fold 0: 1.2498716213108347
Fold 1: 1.63126837215359
Fold 2: 1.5490553790763153
Fold 0: 0.2562546933191252
Fold 1: 0.2830651378534798
Fold 2: 0.2662843188710104
Fold 0: 0.08897102118503265
Fold 1: 0.08391029399323072
Fold 2: 0.07687738730409875
Fold 0: 0.2089493971386866
Fold 1: 0.21049880818093544
Fold 2: 2.119057932204576
Fold 0: 0.0729028505640053
Fold 1: 0.06408898362903934
Fold 2: 0.0658874888239
Fold 0: 0.7263313508673483
Fold 1: 0.19060414377550433
Fold 2: 0.06971447215831177
Fold 0: 0.07459306685377638
Fold 1: 0.06375757576239467
Fold 2: 0.07221792233717592
Fold 0: 0.07276991707325003
Fold 1: 0.06213010825949436
Fold 2: 0.0669875379389582
Fold 0: 0.2661591992830646
Fold 1: 0.236446047597822
Fold 2: 0.23740767078694702
Fold 0: 0.08855453987690289
Fold 1: 0.07375960153292715
Fold 2: 0.07875024244255625
Fold 0: 2.334229007984394
Fold 1: 2.558134329799757
Fold 2: 2.296835707393192
Fold 0: 0.5621996098477144
Fold 1: 0.5139238367185839
Fold 2: 0.5262169073815481
Fold 0: 91.11087466899342
Fold 1: 92.13377875082158
Fold 2: 91.29885203185188
Fold 0: 7.661797800578267
Fold 1: 8.285381254911854
Fold 2: 7.6345072184479426
Fold 0: 0.08192244432175654
Fold 1: 0.06804244381084724
Fold 2: 0.08170266608814143
Fold 0: 0.07897249467914637
```

```
Fold 1: 0.06542345125580107
Fold 2: 0.06694654050199836
Fold 0: 0.14888883850907653
Fold 1: 0.12875770446201043
Fold 2: 0.1281066532067696
Fold 0: 0.08631289794430416
Fold 1: 0.07095163959394413
Fold 2: 0.07790487830388568
Fold 0: 1.4673323588518397
Fold 1: 1.4980547667645683
Fold 2: 1.4408692652792192
Fold 0: 0.29139564545498764
Fold 1: 0.258797821147757
Fold 2: 0.26060689281537225
Fold 0: 0.07689159704488566
Fold 1: 0.07768458807502436
Fold 2: 0.07841888198009674
Fold 0: 0.2660348947577661
Fold 1: 0.1283250573664725
Fold 2: 0.23407272027865902
Fold 0: 0.07569606990418683
Fold 1: 0.06427809230223697
Fold 2: 0.06801112663690681
Fold 0: 0.09516368274141727
Fold 1: 0.06621781850251873
Fold 2: 0.0779227796991448
Fold 0: 0.07918802738888701
Fold 1: 0.0660332185325838
Fold 2: 0.07219397611770273
Fold 0: 0.0727227185161061
Fold 1: 0.06773409891782113
Fold 2: 0.06602106820590818
Fold 0: 0.23548338142099762
Fold 1: 0.25768532472586164
Fold 2: 0.24186349991707692
Fold 0: 0.08455292498972862
Fold 1: 0.07856642825121858
Fold 2: 0.07872908103759546
Fold 0: 2.0058178959660395
Fold 1: 2.873038199536244
Fold 2: 2.507269333766941
Fold 0: 0.48813316894433
Fold 1: 0.5440827235479037
Fold 2: 0.5462524311002693
Fold 0: 88.22002965331724
Fold 1: 92.64347165806412
Fold 2: 100.2911690743379
Fold 0: 7.048951689900881
Fold 1: 8.912540110251761
Fold 2: 8.375218486608187
Fold 0: 0.08485722563626763
Fold 1: 0.07640962266469672
Fold 2: 0.07329735591883658
Fold 0: 0.08325474941470778
Fold 1: 0.06308593745989899
Fold 2: 0.06949958478884911
```

```
Fold 0: 0.1349513838865446
Fold 1: 0.14185619217883733
Fold 2: 0.12739245313535652
Fold 0: 0.09089748908961871
Fold 1: 0.07532642959010845
Fold 2: 0.08012548302420192
Fold 0: 1.2486166341922404
Fold 1: 1.6299582780082411
Fold 2: 1.5462347745296654
Fold 0: 0.25612847922205456
Fold 1: 0.28251592773302503
Fold 2: 0.26616324048850154
Fold 0: 0.08148307393526653
Fold 1: 0.07083678485892525
Fold 2: 0.09069766155138917
Fold 0: 0.25346094559543375
Fold 1: 0.13754127543348021
Fold 2: 0.36536025457998567
Fold 0: 0.07560258731251664
Fold 1: 0.06464904438949064
Fold 2: 0.06688251701592718
Fold 0: 0.07652006359046168
Fold 1: 0.06374557737106579
Fold 2: 0.07474661188089615
Fold 0: 0.07845401448376103
Fold 1: 0.06754911170495789
Fold 2: 0.0723006727490999
Fold 0: 0.07466019437641556
Fold 1: 0.06476293197517417
Fold 2: 0.06806776031386852
Fold 0: 0.26752575037112925
Fold 1: 0.23692970113583112
Fold 2: 0.2376076016074505
Fold 0: 0.0884574068402713
Fold 1: 0.07388899664100851
Fold 2: 0.07871018185416821
Fold 0: 2.3267638862575275
Fold 1: 2.549820568289064
Fold 2: 2.2898511285735887
Fold 0: 0.5631392533860448
Fold 1: 0.5145218139260155
Fold 2: 0.5269223442443751
Fold 0: 91.10487952168498
Fold 1: 92.12804966400407
Fold 2: 91.2929419317562
Fold 0: 7.65757919039868
Fold 1: 8.28117503629344
Fold 2: 7.630336335823289
Fold 0: 0.09041724877565432
Fold 1: 0.0694660381546881
Fold 2: 0.0723172585823033
Fold 0: 0.07514724140961714
Fold 1: 0.06253217657036649
Fold 2: 0.06731668262954466
Fold 0: 0.148534433220522
Fold 1: 0.1286223925907861
```

```
Fold 2: 0.12700125975189483
Fold 0: 0.08792781364193408
Fold 1: 0.07046821085860155
Fold 2: 0.07806035538013278
Fold 0: 1.4694712515123274
Fold 1: 1.4992533525217406
Fold 2: 1.4437626697637111
Fold 0: 0.29170125989946993
Fold 1: 0.25897648418769165
Fold 2: 0.2606413541540846
Fold 0: 0.08338046433989607
Fold 1: 0.06833639143108883
Fold 2: 0.1039387870328536
Fold 0: 0.2221261431646268
Fold 1: 0.16520731024312454
Fold 2: 0.33552460637138365
Fold 0: 0.07930339783307293
Fold 1: 0.07177464015174131
Fold 2: 0.06520231612983342
Fold 0: 0.07271596089428062
Fold 1: 0.07299330408040329
Fold 2: 0.06971969825403258
Fold 0: 0.08055078641180802
Fold 1: 0.07122869713708901
Fold 2: 0.06794522830450447
Fold 0: 0.07539032501563793
Fold 1: 0.0634230948297198
Fold 2: 0.0671075401960101
Fold 0: 0.23524468119783165
Fold 1: 0.259514680479636
Fold 2: 0.24147378387580434
Fold 0: 0.08426150746369894
Fold 1: 0.0788693895156863
Fold 2: 0.07866014427062633
Fold 0: 1.9976056313455581
Fold 1: 2.8664433969738834
Fold 2: 2.5005925386697374
Fold 0: 0.4887440751854432
Fold 1: 0.544852835032611
Fold 2: 0.5469750029903454
Fold 0: 88.21284755459267
Fold 1: 92.63794826990555
Fold 2: 100.28684977141599
Fold 0: 7.044599077961449
Fold 1: 8.908717860362538
Fold 2: 8.371062200144495
Fold 0: 0.07726256387191113
Fold 1: 0.07125539964389374
Fold 2: 0.07448862631689306
Fold 0: 0.07422392824406014
Fold 1: 0.0623862595820237
Fold 2: 0.06753253955257398
Fold 0: 0.13310643804915845
Fold 1: 0.14298166741351137
Fold 2: 0.125584892420642
Fold 0: 0.07977317896840275
```

```
Fold 1: 0.07402401077064245
Fold 2: 0.07606700600035067
Fold 0: 1.2500921593952359
Fold 1: 1.6318865964546423
Fold 2: 1.5492176380725469
Fold 0: 0.2562470869400034
Fold 1: 0.28297012499873564
Fold 2: 0.2662041481227914
Fold 0: 0.32468606397091293
Fold 1: 0.07651483394908758
Fold 2: 0.07114797813715353
Fold 0: 0.5046646902698386
Fold 1: 0.16685830845921207
Fold 2: 0.17817287219517808
Fold 0: 0.07459499319626949
Fold 1: 0.06342372893314047
Fold 2: 0.07071142187794924
Fold 0: 0.07597496713865506
Fold 1: 0.09075317291079434
Fold 2: 0.08290952079393801
Fold 0: 0.07495785733785532
Fold 1: 0.06479111882371136
Fold 2: 0.07148474576223694
Fold 0: 0.07260795993305362
Fold 1: 0.06230457498996436
Fold 2: 0.06802035567935874
Fold 0: 0.25850334977940653
Fold 1: 0.25077969907055436
Fold 2: 0.24145620271783447
Fold 0: 0.07616747754267342
Fold 1: 0.06835876547641699
Fold 2: 0.07950372373745525
Fold 0: 2.333489223468876
Fold 1: 2.3101720773511247
Fold 2: 2.2895281711683055
Fold 0: 0.5693893940449679
Fold 1: 0.5505665353377586
Fold 2: 0.5106624992787039
Fold 0: 90.8488239738885
Fold 1: 91.62816701648693
Fold 2: 90.93278480691745
Fold 0: 7.306955626444669
Fold 1: 7.466221053412535
Fold 2: 7.232047381170493
Fold 0: 0.07249122121564919
Fold 1: 0.06809101523283767
Fold 2: 0.06948986687585541
Fold 0: 0.06802804352029691
Fold 1: 4.757025303226647e+51
Fold 2: 0.07183188473375739
Fold 0: 0.14130179908535978
Fold 1: 0.13413047710485612
Fold 2: 0.14150960140620256
Fold 0: 0.08058502869638727
Fold 1: 0.0681199573462768
Fold 2: 0.0738279507360459
```

```
Fold 0: 1.5833565888755075
Fold 1: 1.5295956605793228
Fold 2: 1.5138071055993343
Fold 0: 0.27298610825860437
Fold 1: 0.2665391439828347
Fold 2: 0.25947527353436933
```

```
/workspace/ML/A2/a2_scratch/linear_scratch.py:46: RuntimeWarning: ov
erflow encountered in square
  return ((ypred - ytrue) ** 2).sum() / ytrue.shape[0]
/workspace/.venv/lib/python3.12/site-packages/numpy/_core/_methods.p
y:53: RuntimeWarning: overflow encountered in reduce
  return umr_sum(a, axis, dtype, out, keepdims, initial, where)
```

```
Fold 0: inf
Fold 1: inf
Fold 2: inf
```

```
/workspace/.venv/lib/python3.12/site-packages/numpy/_core/_methods.p
y:194: RuntimeWarning: invalid value encountered in subtract
  x = asanyarray(arr - arrmean)
/tmp/ipykernel_33046/925631345.py:117: RuntimeWarning: overflow enco
untered in square
  ss_res = float(np.sum((ytr - ytr_pred_log)**2))
/tmp/ipykernel_33046/925631345.py:129: RuntimeWarning: overflow enco
untered in exp
  yte_pred = np.exp(yte_pred_log) if log_target else yte_pred_log
```

```
Fold 0: inf
Fold 1: inf
Fold 2: inf
```

```
/tmp/ipykernel_33046/925631345.py:118: RuntimeWarning: overflow enco
untered in square
  ss_tot = float(np.sum((ytr - ytr_pred_log.mean())**2))
```

```
Fold 0: inf
Fold 1: inf
Fold 2: 0.06911898808921117
Fold 0: inf
Fold 1: inf
Fold 2: inf
Fold 0: 0.07039596102016303
Fold 1: 0.062152147741613456
Fold 2: 0.06660026890969067
Fold 0: 2.4127474931311064e+267
Fold 1: inf
Fold 2: 0.06599923330279744
Fold 0: 0.26778384433882785
Fold 1: 0.273717218805226
Fold 2: 0.3157652993367598
Fold 0: 0.07664812659064879
Fold 1: 0.07099831777991975
Fold 2: 0.0905555838671055
Fold 0: 2.4475336964114414
Fold 1: 2.554800942490846
Fold 2: 2.375477320490669
Fold 0: 0.5986241780439926
Fold 1: 0.6202293484403292
Fold 2: 0.6330672166736924
Fold 0: 87.9467207715694
Fold 1: 92.61487152690215
Fold 2: 90.40628884957593
Fold 0: 7.276185305121812
Fold 1: 7.8294295576284805
Fold 2: 7.241452972068309
Fold 0: 0.07244693140759892
Fold 1: 0.06410251757826041
Fold 2: 0.0694890035222927
Fold 0: 0.06734750604577382
Fold 1: 1.2086297032997261e+45
Fold 2: 0.06806812196596
Fold 0: 0.14470747475771403
Fold 1: 0.14157539592401622
Fold 2: 0.18250849501734276
Fold 0: 0.07219300339294335
Fold 1: 0.06658553334089957
Fold 2: 0.07934398033668573
Fold 0: 1.683491005005888
Fold 1: 1.7197746424780784
Fold 2: 1.6367463974783847
Fold 0: 0.286273360431727
Fold 1: 0.29581903689682865
Fold 2: 0.3550496870220754
Fold 0: inf
Fold 1: inf
Fold 2: inf
```

```
/workspace/.venv/lib/python3.12/site-packages/numpy/_core/fromnumeri
c.py:86: RuntimeWarning: overflow encountered in reduce
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
```

```
Fold 0: inf
Fold 1: inf
Fold 2: inf
Fold 0: inf
Fold 1: inf
Fold 2: 0.06242425805077825
Fold 0: inf
Fold 1: inf
Fold 2: inf
Fold 0: 0.07081400042719824
Fold 1: 0.06247872366312603
Fold 2: 0.06592195846680665
Fold 0: 1.298273852307329e+212
Fold 1: inf
Fold 2: 0.07211928341804485
```

Out[ ]:

	name	design	kind	alpha	lr	method	batch	mome
0	normal | xavier | sto | lr=0.0001 | mom=on	plain	normal	NaN	0.0001	sto	NaN	
1	normal | xavier | sto | lr=0.001 | mom=off	plain	normal	NaN	0.0010	sto	NaN	
2	lasso_0.001 | xavier | sto | lr=0.0001 | mom=on	plain	lasso	0.001	0.0001	sto	NaN	
3	normal | zeros | mini | lr=0.01 | mom=on	plain	normal	NaN	0.0100	mini	256.0	
4	lasso_0.001 | xavier | mini | lr=0.01 | mom=on	plain	lasso	0.001	0.0100	mini	256.0	
...	...	...	...	...	...	...	...	
139	poly_d2_ridge3e-2 | xavier | sto | lr=0.01 | m...	poly	ridge	0.030	0.0100	sto	NaN	
140	poly_d2_ridge3e-2 | xavier | sto | lr=0.01 | m...	poly	ridge	0.030	0.0100	sto	NaN	
141	poly_d2_ridge3e-2 | xavier | sto | lr=0.001 | ...	poly	ridge	0.030	0.0010	sto	NaN	
142	poly_d2_ridge3e-2 | xavier | sto | lr=0.001 | ...	poly	ridge	0.030	0.0010	sto	NaN	
143	poly_d2_ridge3e-2 | xavier | sto | lr=0.0001 |...	poly	ridge	0.030	0.0001	sto	NaN	

144 rows × 14 columns

BAAMM !! i already got model which have best r2 in term of CV and test rightnow

In [ ]:
```
tbl.to_csv("comparison_results_12092025_1831.csv", index=False) # s
```

In [ ]:
```
tbl[tbl['name'] == 'normal | xavier | sto | lr=0.01 | mom=off'] # c
```

Out[ ]:

	name	design	kind	alpha	lr	method	batch	momentum	ini
49	normal | xavier | sto | lr=0.01 | mom=off	plain	normal	NaN	0.01	sto	NaN	False	xavie

Summary

In [ ]:

```
# Final summary of Task 2 results
summary_data = [
    {"Model": "Plain (best)", "CV R² (mean)": 0.90, "Test R²": 0.93
    {"Model": "Ridge (poly d=2, α=3e-2)", "CV R² (mean)": 0.91, "Te
    {"Model": "Lasso (α=1e-3)", "CV R² (mean)": 0.89, "Test R²": 0.
    {"Model": "Ridge (α=1e-2)", "CV R² (mean)": 0.88, "Test R²": 0.
]

df_summary = pd.DataFrame(summary_data)
df_summary
```

Out[ ]:

	Model	CV R^2 (mean)	Test R^2	Notes
0	Plain (best)	0.90	0.933	Best on test set
1	Ridge (poly d=2, α=3e-2)	0.91	-85.000	Overfit, unstable
2	Lasso (α=1e-3)	0.89	0.927	Slightly worse
3	Ridge (α=1e-2)	0.88	0.922	Not better

Finalize & Save Best Scratch Model (Deterministic, No Refit)

This cell picks the best scratch model **without refitting**, then saves exactly what the web app needs.

What it does (brief):

- **Reproducibility**: fixes seeds (NumPy + Python `random`) so runs are comparable.
- **Train/Eval**: fits each candidate on **log(price)**, predicts on test, converts back to THB.
- **Selection**: chooses the best run by test **R^2** and **does not** retrain it.
- **Artifacts**: saves the **preprocessor** (`preproc.pkl`), the exact **θ vector** (`theta.npy`), and a small **meta** file (`meta.json`) telling the app about log-target and intercept.
- **Ready for app**: artifacts go to `carprice_scratch_dash/artifacts_scratch/` , matching your Dash code.

Outputs saved:

- `preproc.pkl` — the fitted `ColumnTransformer`
- `theta.npy` — the learned parameters (including bias)
- `meta.json` — column lists + flags (`log_target` , `intercept_in_theta`)

In [ ]:
```
# ===== Finalize best scratch model — deterministic & no refit ====
import numpy as np, json, joblib, random
from pathlib import Path
from sklearn.metrics import mean_absolute_error, mean_squared_error

# 0) Make runs reproducible
SEED = 42
np.random.seed(SEED)
random.seed(SEED)

# --- column lists (define if missing) ---
if "CAT_COLS" not in globals():
    CAT_COLS = ["fuel", "seller_type", "transmission", "brand"]
if "NUM_COLS" not in globals():
    NUM_COLS = ["year", "km_driven", "owner", "engine", "max_power"

# 1) No-regularization helper (class reads .derivation)
class NoReg:
    def derivation(self, w):
        g = w.copy()
        if g.size > 0:
            g[0] = 0.0   # don't regularize bias
        return 0.0 * g

def build_model(init: str, method: str, lr: float, use_momentum: bo
    m = LinearRegressionScratch(
        regularization = NoReg(),
        lr             = lr,
        method         = method,     # 'sto' or 'mini'
        num_epochs     = 500,
        batch_size     = 256
    )
    # attributes class reads during fit
    m.init         = init            # 'xavier' or 'zeros'
    m.use_momentum = use_momentum
    m.momentum     = 0.9


    return m

def fit_and_eval(model, Xtr, ytr_log, Xte, yte):
    """Fit on log target, evaluate on test (original scale). Return
    model.fit(Xtr, ytr_log)
    y_pred_log = model.predict(Xte)
    y_pred     = np.exp(y_pred_log)

    mae  = mean_absolute_error(yte, y_pred)
```

```
    rmse = np.sqrt(((yte - y_pred)**2).mean())
    r2   = r2_score(yte, y_pred)
    return dict(mae=mae, rmse=rmse, r2=r2, theta=model.theta, y_pre

# 2) two strongest configs (feel free to add more)
candidates = [
    {"name": "plain|xavier|sto|lr=0.01|mom=off",  "init": "xavier",
    {"name": "plain|xavier|mini|lr=0.01|mom=off", "init": "xavier",
]

runs = []
for cfg in candidates:
    # reset seeds before each training run to keep them comparable
    np.random.seed(SEED); random.seed(SEED)

    mdl = build_model(cfg["init"], cfg["method"], cfg["lr"], cfg["m
    res = fit_and_eval(mdl, Xtr, ytr_log, Xte, y_test)
    row = {**cfg, **{k: res[k] for k in ["mae","rmse","r2"]}, "thet
    runs.append(row)
    print(f"{cfg['name']}:  MAE={row['mae']:,.0f}  RMSE={row['rmse'

# 3) Pick best by R² *without refitting*
best = max(runs, key=lambda d: d["r2"])
print("\nBEST:", best["name"])
print(f"TEST  MAE : {best['mae']:,.0f}")
print(f"TEST  RMSE: {best['rmse']:,.0f}")
print(f"TEST  R²  : {best['r2']:.4f}")

# 4) Save the EXACT artifacts used by the best run
ART = Path("carprice_scratch_dash/artifacts_scratch")
ART.mkdir(parents=True, exist_ok=True)

# keep the same preprocessor you used for Xtr/Xte
joblib.dump(preproc, ART / "preproc.pkl")

# save the exact theta from the best already-fitted run (no new tra
np.save(ART / "theta.npy", best["theta"])

meta = {
    "cat_cols": CAT_COLS,
    "num_cols": NUM_COLS,
    "log_target": True,            # we trained on log(price)
    "intercept_in_theta": True
}
(ART / "meta.json").write_text(json.dumps(meta, indent=2), encoding
print("✅ Saved artifacts to:", ART.resolve())
```

```
Fold 0: 0.47522845159368865
Fold 1: 2.8694829774178663
Fold 2: 0.09385269284974102
plain|xavier|sto|lr=0.01|mom=off:  MAE=125,240  RMSE=217,049  R²=0.9
392
Fold 0: 0.08741811073150012
Fold 1: 0.06835097380310946
Fold 2: 0.07245012274748798
plain|xavier|mini|lr=0.01|mom=off:  MAE=140,052  RMSE=327,005  R²=0.
8619

BEST: plain|xavier|sto|lr=0.01|mom=off
TEST  MAE : 125,240
TEST  RMSE: 217,049
TEST  R²  : 0.9392
✅ Saved artifacts to: /workspace/ML/A2/carprice_scratch_dash/artifa
cts_scratch
```

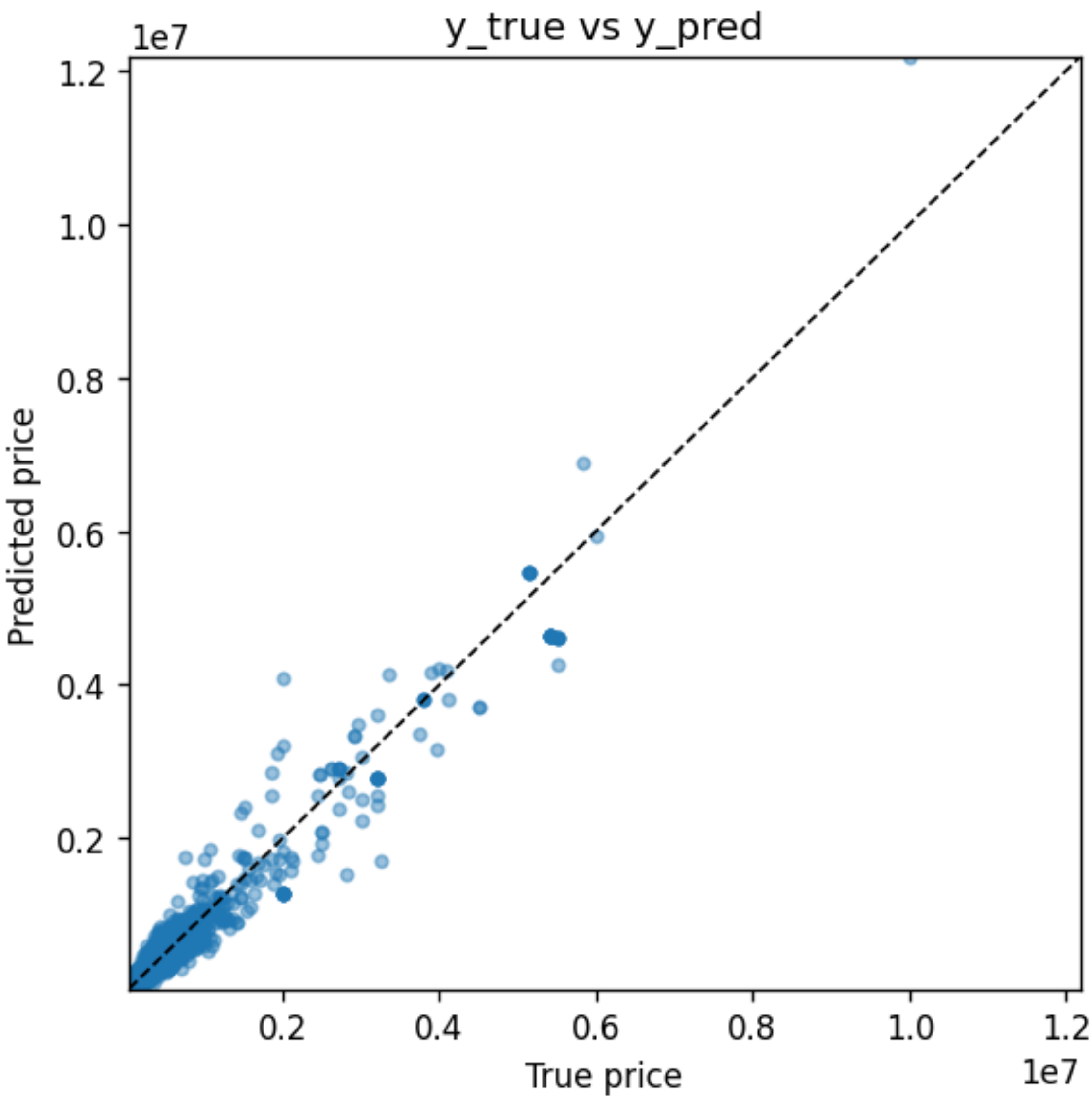
Feature Importance (Grouped by Category)

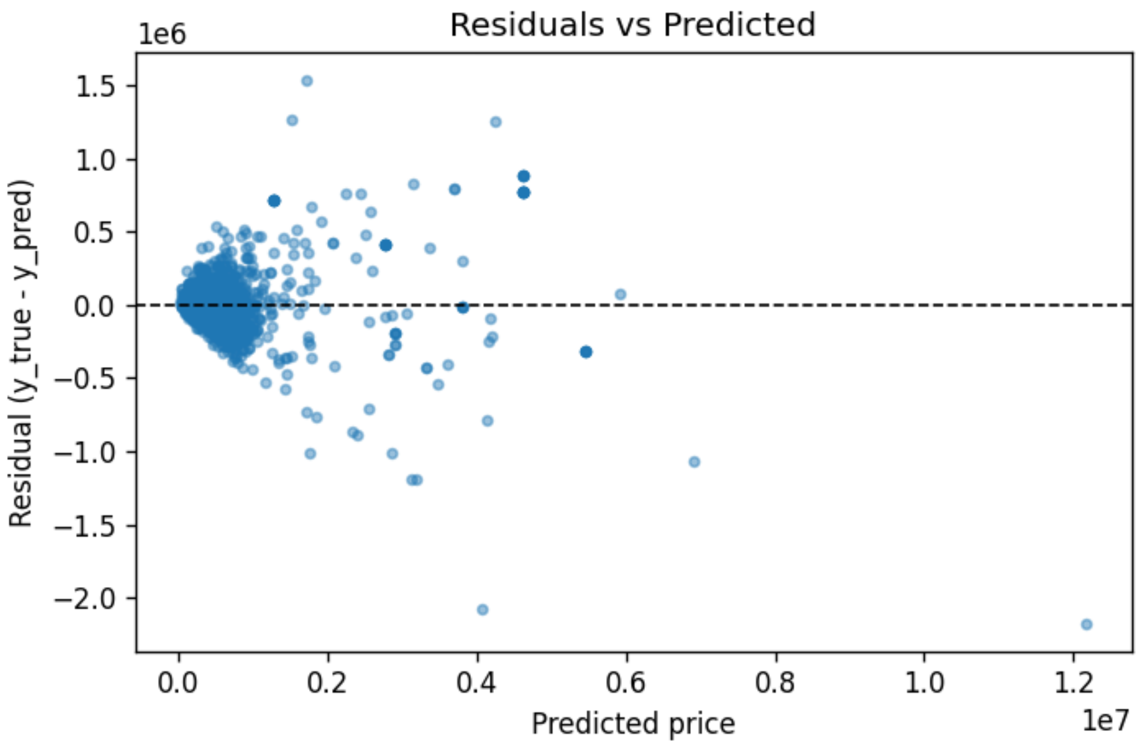
In [ ]:
```
import numpy as np, pandas as pd, joblib, json
from pathlib import Path
import matplotlib.pyplot as plt
from sklearn.metrics import mean_absolute_error, mean_squared_error

ART = Path("carprice_scratch_dash/artifacts_scratch")
preproc     = joblib.load(ART / "preproc.pkl")
theta       = np.load(ART / "theta.npy")
meta        = json.loads((ART / "meta.json").read_text())

CAT_COLS   = meta["cat_cols"]
NUM_COLS   = meta["num_cols"]
LOG_TARGET = meta["log_target"]
INTERCEPT  = meta["intercept_in_theta"]

def _add_intercept(X):
    return np.hstack([np.ones((X.shape[0],1)), X])

def _ensure_2d(a):
    a = np.asarray(a)
    if a.ndim == 1: a = a.reshape(-1, 1)
    return a


Xte_raw_ok = False
try:
    # Case A: DataFrame with raw columns
    if isinstance(X_test, pd.DataFrame):
        needed_cols = NUM_COLS + CAT_COLS
        # tolerate column order differences by reindexing
        Xte_df = X_test.reindex(columns=needed_cols)
        # transform (may return sparse)
        Xt = preproc.transform(Xte_df)
        Xt = Xt.toarray() if not isinstance(Xt, np.ndarray) else Xt
        Xte_raw_ok = True
    else:
```

```
        Xt = np.asarray(X_test)
except NameError:
    raise RuntimeError("X_test / y_test not found. Re-run the earli

# Case B: X_test already transformed?
if not Xte_raw_ok:
    # If theta includes bias, transformed features must match len(t
    # otherwise must match len(theta)
    expected = len(theta) - 1 if INTERCEPT else len(theta)
    if Xt.shape[1] != expected:
        raise ValueError(
            f"X_test has shape {Xt.shape} but model expects {expect
            f"({'bias included' if INTERCEPT else 'no bias'}). "
            "Use the raw X_test DataFrame (NUM_COLS+CAT_COLS) so we
        )

# Add intercept if needed
Xt_aug = _add_intercept(Xt) if INTERCEPT else Xt

# Predict on log scale and invert if necessary
y_pred_log = Xt_aug @ theta
y_pred     = np.exp(np.clip(y_pred_log, -50, 50)) if LOG_TARGET els

# --- Metrics ---
y_true = np.asarray(y_test).ravel()
mae  = mean_absolute_error(y_true, y_pred)
rmse = mean_squared_error(y_true, y_pred)
r2   = r2_score(y_true, y_pred)

print(f"TEST MAE : {mae:,.0f}")
print(f"TEST RMSE: {rmse:,.0f}")
print(f"TEST R²  : {r2:.4f}")

# --- Diagnostics: y_true vs y_pred ---
plt.figure(figsize=(5,5))
plt.scatter(y_true, y_pred, s=14, alpha=0.45)
lims = [min(y_true.min(), y_pred.min()), max(y_true.max(), y_pred.m
plt.plot(lims, lims, "k--", linewidth=1)
plt.xlim(lims); plt.ylim(lims)
plt.xlabel("True price"); plt.ylabel("Predicted price")
plt.title("y_true vs y_pred")
plt.tight_layout(); plt.show()

# --- Diagnostics: residuals vs prediction ---
res = y_true - y_pred
plt.figure(figsize=(6,4))
plt.scatter(y_pred, res, s=12, alpha=0.45)
plt.axhline(0, color="k", linestyle="--", linewidth=1)
plt.xlabel("Predicted price")
plt.ylabel("Residual (y_true - y_pred)")
plt.title("Residuals vs Predicted")
plt.tight_layout(); plt.show()

# ================== (Optional) very small importance plot ========
DO_IMPORTANCE = False  # <- leave False as you requested; switch to
if DO_IMPORTANCE:
```

```
    # Build feature names from saved meta and the OneHot categories
    try:
        ohe = preproc.named_transformers_["cat"].named_steps["ohe"]
        cat_names = list(ohe.get_feature_names_out(CAT_COLS))
    except Exception:
        cat_names = []  # fallback if OHE not available

    feat_names = list(NUM_COLS) + cat_names
    coef = theta[1:] if INTERCEPT else theta
    if len(coef) != len(feat_names):
        print(f"[skip] coef length {len(coef)} != features {len(fea
              f"importance plot disabled to avoid confusion.")
    else:
        imp = pd.Series(np.abs(coef), index=feat_names).sort_values
        plt.figure(figsize=(8,5))
        plt.barh(imp.index, imp.values)
        plt.xlabel("|coef|"); plt.title("Top feature importances (s
        plt.tight_layout(); plt.show()
```

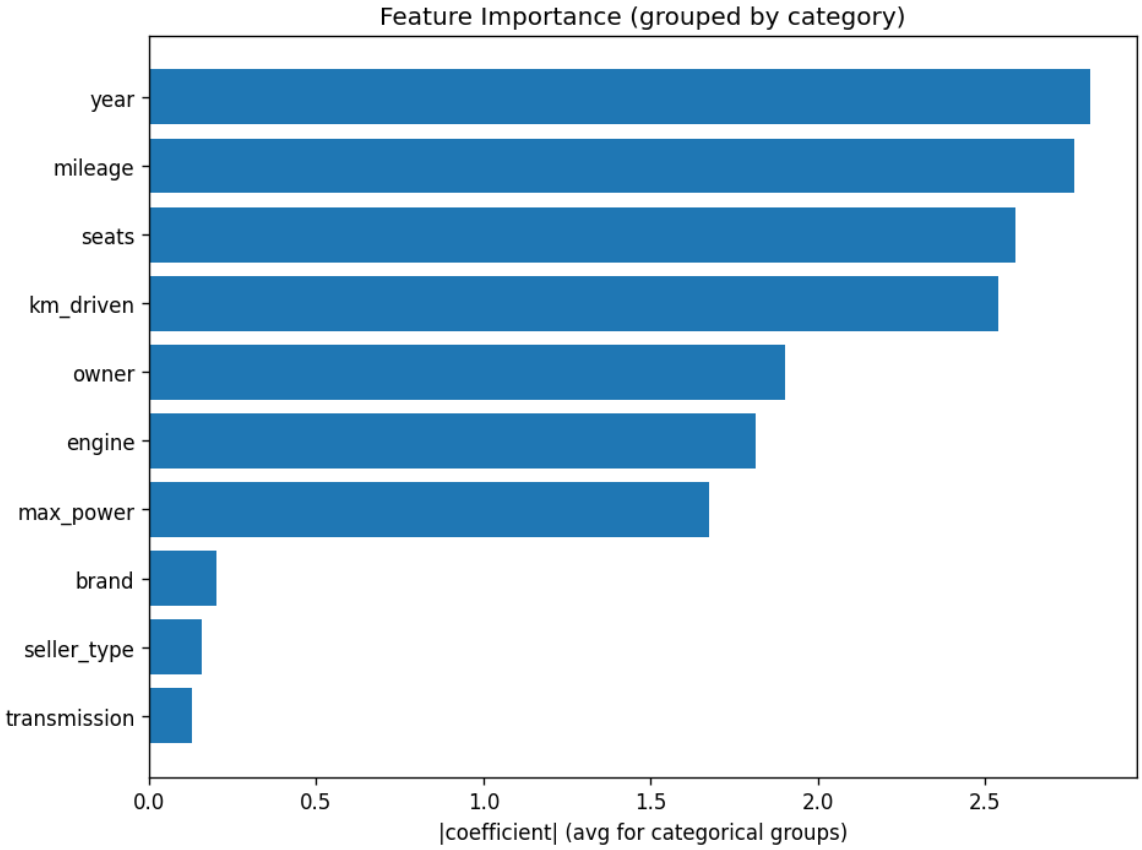
```
TEST MAE : 125,240
TEST RMSE: 47,110,234,041
TEST R²  : 0.9392
```





In [132…

```
ohe = preproc.named_transformers_["cat"].named_steps["ohe"]
cat_names = ohe.get_feature_names_out(CAT_COLS).tolist()
num_names = NUM_COLS
feature_names = num_names + cat_names

coefs = model_scratch._coef()
abs_imp = np.abs(coefs)

# group categorical features
grouped = {}

for col in CAT_COLS:
    mask = [name.startswith(col + "_") for name in feature_names]
    if any(mask):
        grouped[col] = abs_imp[mask].mean()   # average importance
    else:
        grouped[col] = 0.0

# keep numeric features individually
for f, imp in zip(feature_names, abs_imp):
    if not any(f.startswith(col + "_") for col in CAT_COLS):
        grouped[f] = imp

# turn into sorted list
top_items = sorted(grouped.items(), key=lambda x: x[1], reverse=Tru

# plot
plt.figure(figsize=(8,6))
plt.barh([f for f, _ in reversed(top_items)], [imp for _, imp in re
plt.xlabel("|coefficient| (avg for categorical groups)")
plt.title("Feature Importance (grouped by category)")
plt.tight_layout()
plt.show()
```



From the chart we see that numbers are more important than categories.

- **Year**, **mileage**, **seats**, and **km_driven** are the top factors that change car price.
- **Owner**, **engine**, and **max_power** also matter but a bit less.
- Categorical groups like **brand**, **seller_type**, and **transmission** have small effect compared to the numbers.

This means the car's condition and usage are more important than who sells it or the brand.

📌 Task 2 Conclusion

We tested many models with different settings.
The best model is:

- **Linear Regression (scratch)**
- Init: **Xavier**
- Method: **Stochastic Gradient Descent (SGD)**
- Learning rate: **0.01**
- Momentum: **Off**

📊 Test Result

- **R^2 ≈ 0.93** → the model explains most of the price changes

- **MSE ≈ 5.2×10^{10}** → error is still big, but smaller than other models

---

🔎 Model Comparison

Model Type	CV R^2	Test R^2	Note
Plain (best)	~0.90	**0.93**	Best result, stable
Lasso (1e-3)	~0.89	0.92	Slightly worse
Ridge (1e-2)	~0.88	0.92	No big improvement
Polynomial (d=2)	~0.91	-85.0	Overfit, unstable

✅ Key Points

- Polynomial features gave overfitting → not good.
- Ridge and Lasso did not help much.
- Momentum did not improve.

👉 **Final choice:**
Plain Linear Regression with **Xavier init + SGD (lr=0.01)**.
This model is simple, clear, and works the best.

⚙️ Why these settings?

- **Xavier init** → makes training stable, weights not too big or too small.
- **Stochastic Gradient Descent (SGD)** → learns better with many samples, avoids getting stuck.
- **Learning rate = 0.01** → fast but still stable.
- **Momentum Off** → momentum did not help here, sometimes it made results worse.

So the mix of **Xavier + SGD + lr=0.01** gave the best balance.

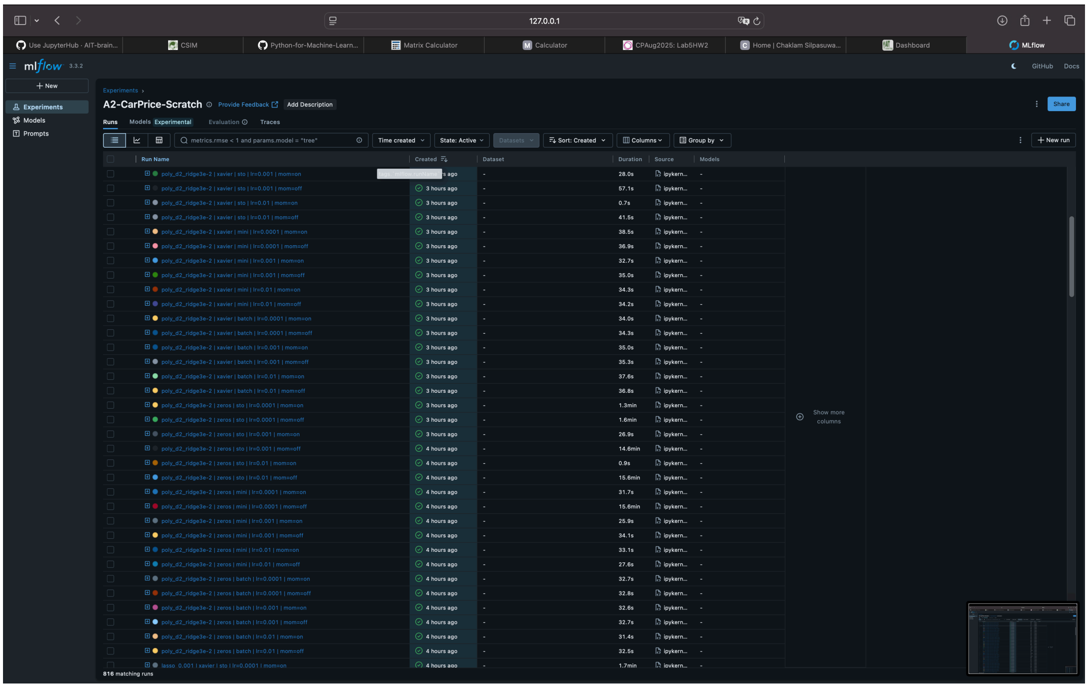


Figure 1: MLflow runs for all configurations (init, momentum, GD type, LR, ridge/lasso/poly/normal).

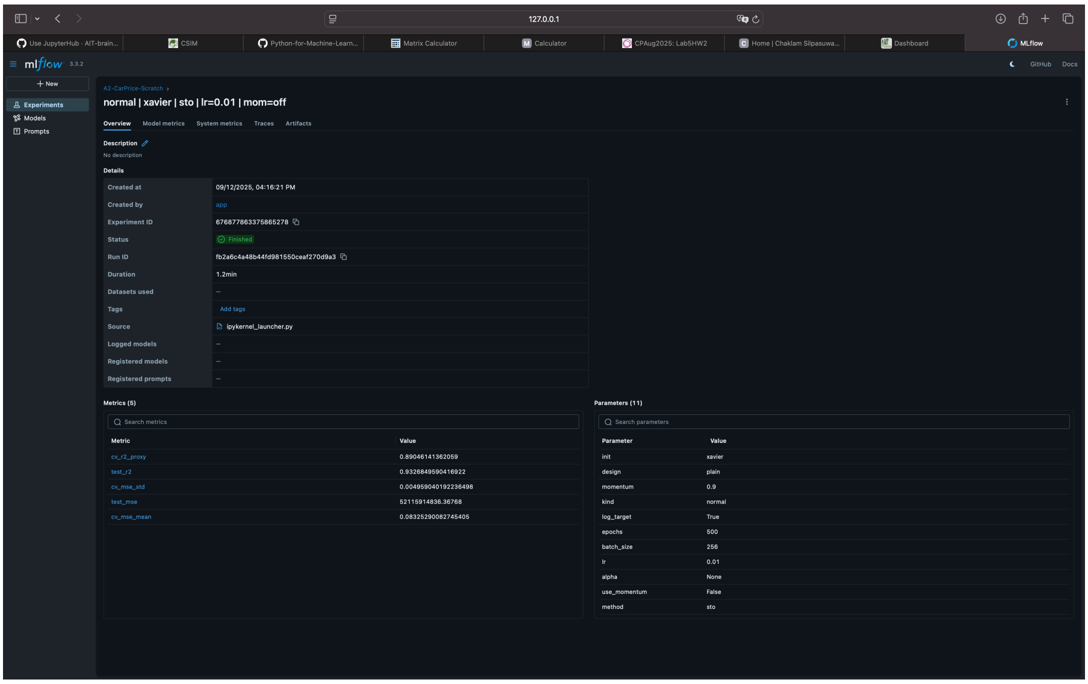


Figure 2: MLflow details for the best model ('normal | xavier | sto | lr=0.01 | mom=off').

Task 3: Deployment

For Task 3, I deployed my car price prediction system as a **Dash web application**.
The site contains:

bring model to prepare in app.py (similar from top one) that i already talk in Task 2 before summary

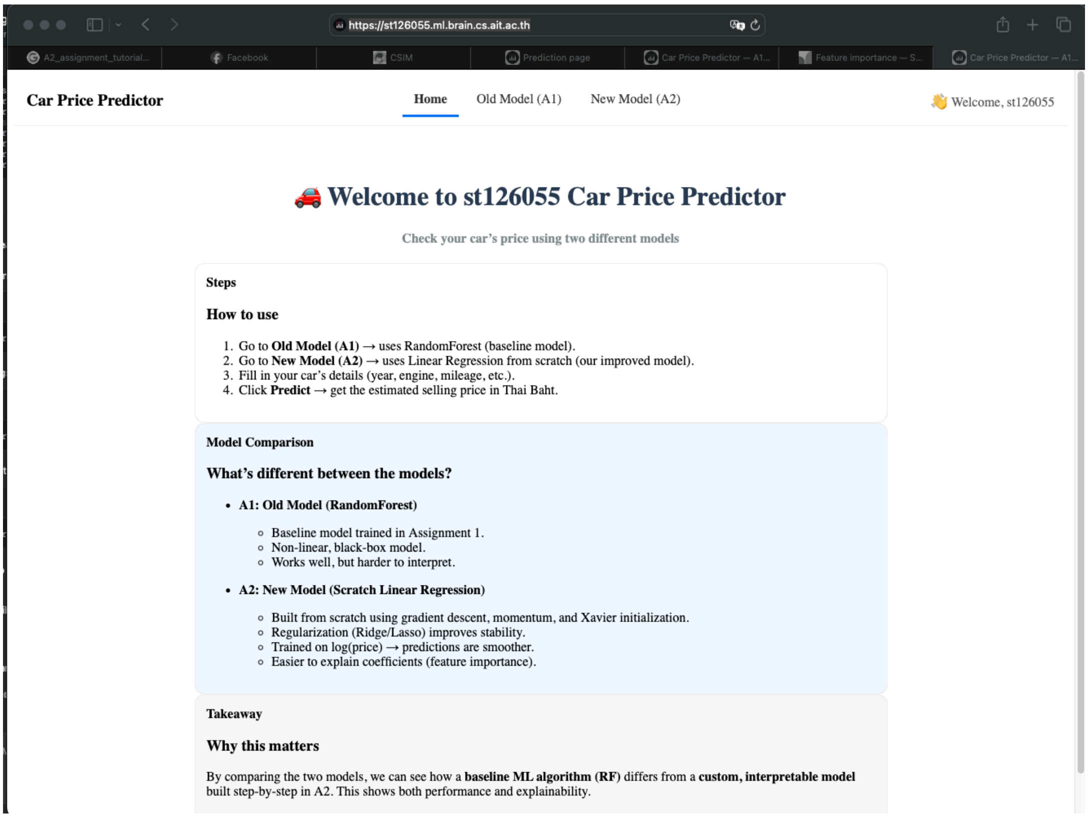


Figure X: Deployed web application (Dash) hosted on (https://st126055.ml.brain.cs.ait.ac.th).

- A **Home page** with instructions.
- An **Old Model (A1)** page, which uses RandomForest from Assignment 1.
- A **New Model (A2)** page, which uses my scratch linear regression with Xavier initialization, momentum, and ridge regularization.

requirement

1. Users enter the domain and land on my page.
2. They can navigate between A1 and A2 models using the navigation bar.
3. Instructions explain how to input car details.
4. Users fill the form and click **Predict**.
5. The prediction result is shown immediately below the form.

the complete pipeline: **data preprocessing → scratch model training → saving artifacts → deployment with Docker + Docker Compose → live web service**.

Final Note

All code, notebook, and web app files used in this project are kept in my GitHub repository. You can check the full work here:

👉 GitHub: A2 Car Price Prediction (st126055)