Car Price Prediction – Phase 2 - Tracking & Model Management with MLflow

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1️⃣ Introduction

Objective of Phase 2

Experiment Overview

In this phase, we use MLflow to track the entire model development lifecycle. This includes:

- Logging key hyperparameters and configuration settings.
- Recording evaluation metrics such as RMSE and R^2.
- Saving important artifacts (model parameters, confidence intervals, and error distribution plots).
- Setting tags for easy filtering (e.g., dataset version, algorithm).
- Registering the best-performing model in the MLflow Model Registry.

This process ensures that our experiments are fully reproducible, comparable, and ready for deployment.

Model Versions in Phase 2

A total of **9 model versions** were developed, each incorporating improvements over the previous version. The key changes are summarized below:

Version	Change	RMSE	R^2
1	Baseline: Linear Regression	*530.56*	*0.9694*
2	Polynomial Features + Ridge Regression	*216.50*	*0.9950*
3	Improved Feature Standardization	*566.83*	*0.9655*
4	Hyperparameter Tuning for Ridge	*565.58*	*0.9657*
5	Comparison of Ridge, Lasso & ElasticNet	*527.72*	*0.9672*
6	Feature Selection with Lasso	*1339.54*	*0.8075*
7	Inclusion of Additional Features (Owner_Count)	*1333.45*	*0.8092*
8	Optimized Model with Best Hyperparameters	*527.82*	*0.9673*
9	Fine-tuning with Lower Lasso Alpha	*792.66*	*0.9326*

Code for initializing MLflow:

```python import mlflow mlflow.set_experiment("Car Price Prediction - Version X")

with mlflow.start_run(): mlflow.log_param("Model", "Ridge") mlflow.log_param("alpha", 1.0) mlflow.log_metric("RMSE", rmse) mlflow.log_metric("R2_Score", r2) mlflow.sklearn.log_model(ridge, "ridge_model_vX")

# MLflow Tracking Details

## Why Use MLflow for Experiment Tracking?

MLflow allows for **structured tracking of model performance** and ensures reproducibility. The key benefits include: ✅ Easy **comparison** of different models
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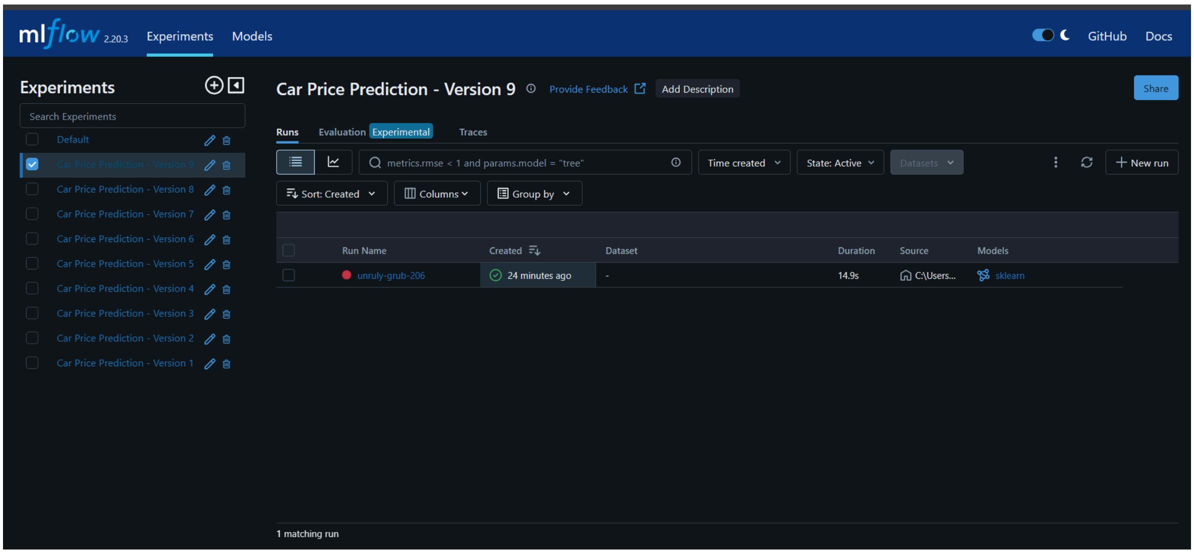
✅ Ability to **restore previous models** and configurations
✅ Centralized **artifact storage** (models, plots, parameters, and metrics)

What Was Logged in MLflow?

Logged Item	Description
Parameters	Model hyperparameters such as `alpha`, `degree` for polynomial features
Metrics	RMSE (Root Mean Squared Error), R^2 (coefficient of determination)
Artifacts	Model files (`.pkl`), confidence interval CSV, plots (residuals, error distribution)
Tags	Model type, dataset version, experiment version

MLflow UI Overview

To view the experiment results, the MLflow UI was launched using:
```bash mlflow ui




## Understanding MLflow Tracking in Depth

### How Are Runs Tracked in MLflow?

Each MLflow run is stored in a **tracking server**, logging:

1. **Parameters:** Hyperparameters such as `alpha`, `polynomial degree`, etc.
2. **Metrics:** RMSE, $R^2$
3. **Artifacts:** Model files, confidence intervals, plots
4. **Tags:** Model type, dataset version

### Retrieving Past Runs from MLflow

```python import mlflow

# Get all experiment runs

runs = mlflow.search_runs() print(runs[["run_id", "metrics.RMSE", "metrics.R2_Score", "params.alpha"]])

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### 🔷 2 Confidence Interval Visualization

- **Insert this after confidence interval calculations**
- **Located after confidence intervals are logged in MLflow.**

## Confidence Intervals - Visualizing Uncertainty

### How to Interpret Confidence Intervals?

A confidence interval (CI) provides an **uncertainty range** for a prediction:

- **Narrow CI → More confident prediction**
- **Wide CI → More uncertainty (fewer data points in that range)**

### Visualizing the Confidence Intervals

```python import numpy as np import statsmodels.api as sm import matplotlib.pyplot as plt import seaborn as sns

# 📌 Calculation of Confidence Intervals with Statsmodels

X_train_sm = sm.add_constant(X_train) # Add intercept ols_model = sm.OLS(y_train, X_train_sm).fit() # Fit OLS model predictions = ols_model.get_prediction(sm.add_constant(X_test)) # Predictions pred_mean = np.expm1(predictions.predicted_mean) # Inverse log transformation conf_int = np.expm1(predictions.conf_int()) # 95% confidence intervals

# Sort values by predicted prices

sorted_indices = np.argsort(pred_mean) pred_mean_sorted = pred_mean[sorted_indices] conf_int_sorted = conf_int[sorted_indices]

plt.figure(figsize=(10, 6)) plt.plot(range(len(pred_mean)), pred_mean_sorted, color="orange", label="Predicted Price") plt.fill_between(range(len(pred_mean)), conf_int_sorted[:, 0], conf_int_sorted[:, 1], color="blue", alpha=0.2, label="95% Confidence Interval") plt.xlabel("Sorted Sample Index") plt.ylabel("Car Price (€)") plt.title("Predicted Prices with 95% Confidence Intervals (Sorted)") plt.legend() plt.show()

sample_size = 100 sample_indices = np.random.choice(len(pred_mean), sample_size, replace=False)

plt.figure(figsize=(10, 6)) plt.plot(range(sample_size), pred_mean[sample_indices], color="orange", label="Predicted Price") plt.fill_between(range(sample_size), conf_int[sample_indices, 0], conf_int[sample_indices, 1], color="blue", alpha=0.2, label="95% Confidence Interval") plt.xlabel("Sample Index") plt.ylabel("Car Price (€)") plt.title("Predicted Prices with 95% Confidence Intervals (Sample of 100)") plt.legend() plt.show()

plt.figure(figsize=(10, 6)) plt.plot(range(len(pred_mean)), pred_mean, color="orange", label="Predicted Price") plt.fill_between(range(len(pred_mean)), conf_int[:, 0], conf_int[:, 1], color="blue", alpha=0.2, label="95% Confidence Interval") plt.xlabel("Sample Index") plt.ylabel("Car Price (€)") plt.ylim([0, 20000]) # Limit y-axis range plt.title("Predicted Prices with 95% Confidence Intervals") plt.legend() plt.show()

## Confidence Interval Visualization and Analysis

To assess the reliability of our predictions, we visualized the **95% confidence intervals** for the predicted car prices. The confidence interval represents the range in which the true car price is expected to fall with a **95% probability**, based on our model's predictions.

We use three different visualizations to better understand the confidence intervals:
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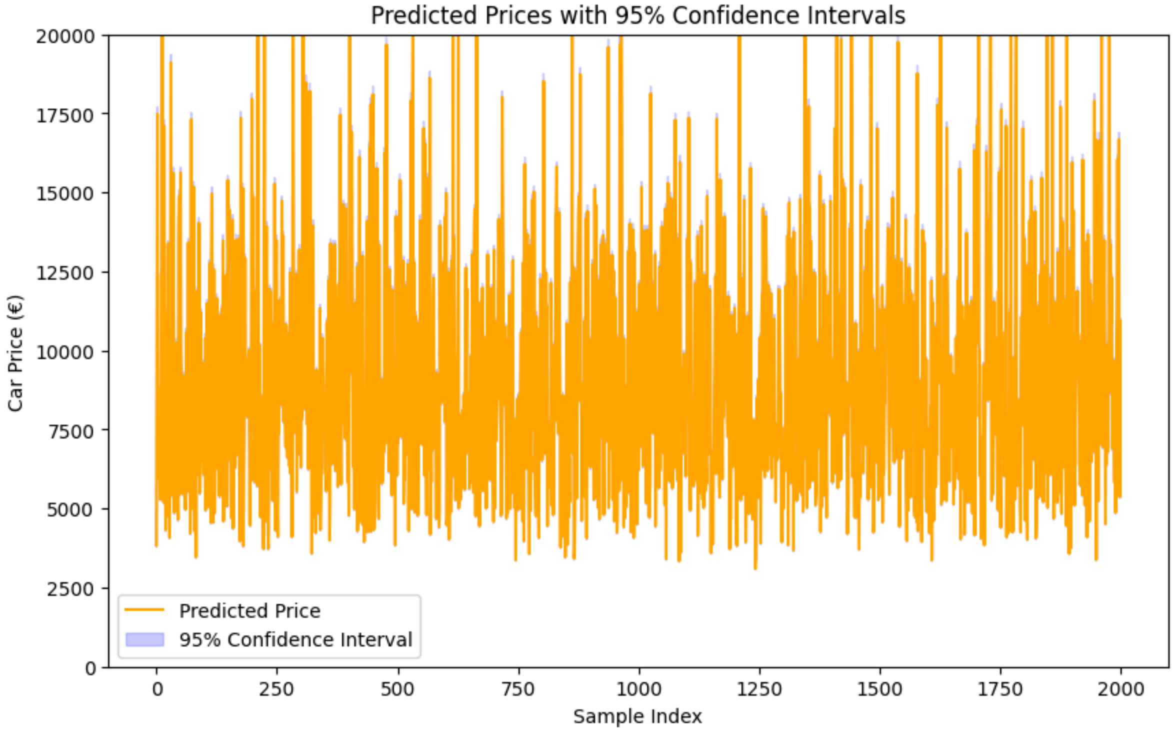
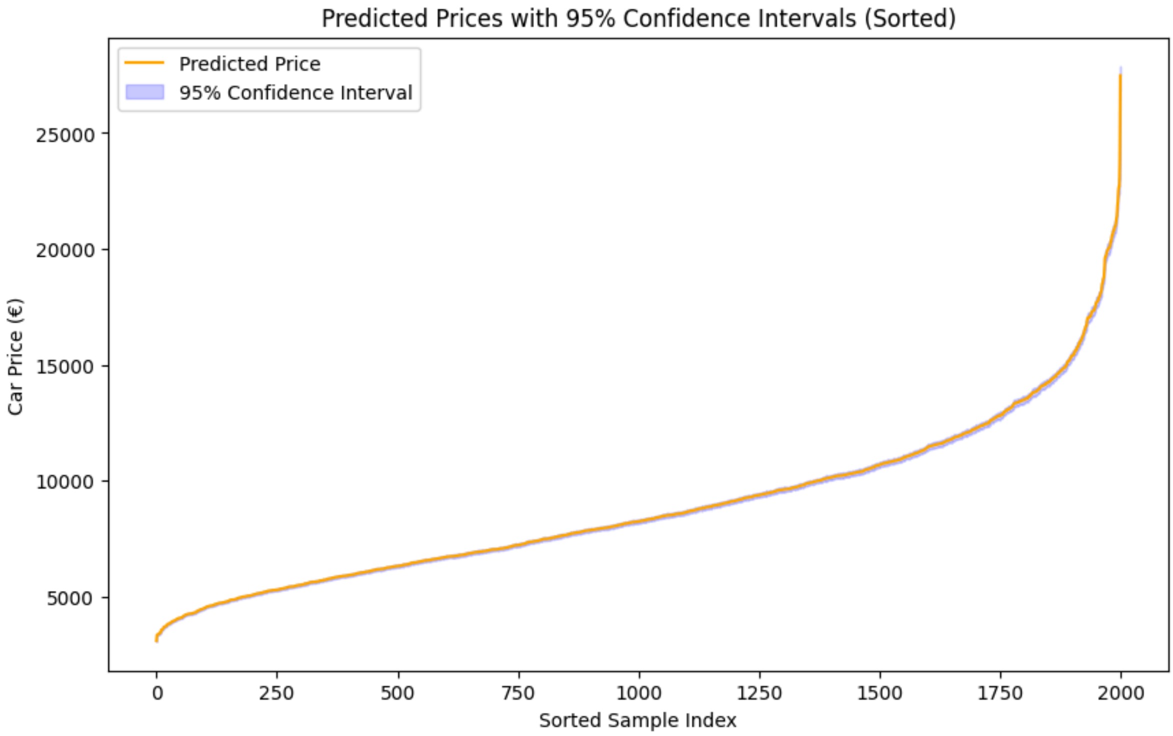
1. **Predicted Prices with 95% Confidence Intervals (Unsorted)**



Analysis:

- The orange line represents the predicted car prices.
- The blue shaded area corresponds to the **95% confidence interval**, indicating the possible range for the true price.
- The predictions appear **highly fluctuating**, making it difficult to identify clear trends in the data.
- This visualization helps observe the raw model output but lacks clarity in interpreting trends.

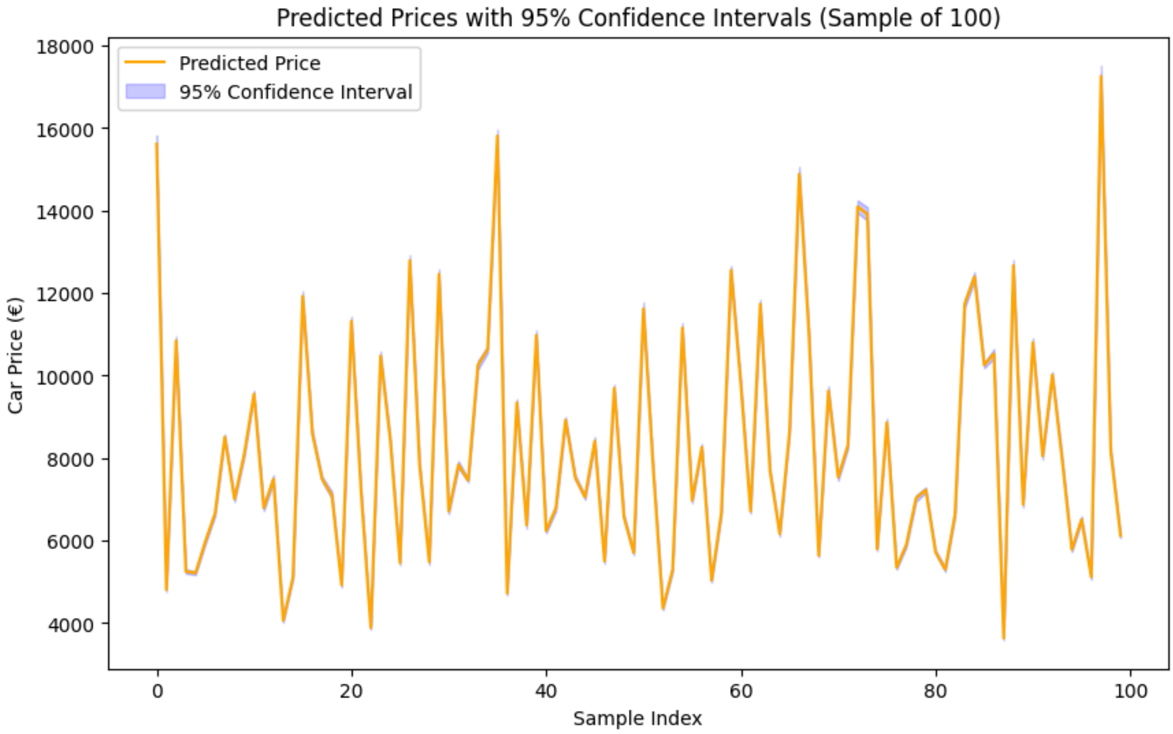
2. **Predicted Prices with 95% Confidence Intervals (Sorted)**



Analysis:

- Here, predictions are sorted in ascending order, allowing us to **clearly visualize the trend** of predicted prices.
- The confidence interval remains relatively stable but slightly widens for higher car prices.
- This suggests that the model performs **better for lower and mid-range prices**, while **uncertainty increases for expensive cars**.
- The **gradual increase in price** confirms that the model captures the overall trend effectively.

3. **Predicted Prices with 95% Confidence Intervals (Sample of 100)**



Analysis:

- This plot visualizes a **random sample of 100 predictions**, making it easier to inspect local variations.
- Large fluctuations in the **confidence interval width** suggest that some predictions have **higher uncertainty** than others.
- Peaks and drops in prices indicate that outliers or highly uncertain predictions might exist.
- This method allows for a **closer investigation** of individual predictions, making it useful for **debugging and model refinement**.

Overall Conclusion:

- The confidence intervals provide insights into the **certainty of the model's predictions**.
- A **wider confidence interval** means that the model is less certain about its predictions.
- Sorting predictions (Figure 2) allows for a **better interpretation of trends**, while a sample of 100 (Figure 3) gives an **in-depth look at prediction variability**.
- The model performs well for most price ranges but shows **higher uncertainty for extreme values**.

These visualizations are crucial for understanding the limitations of the model and identifying areas for **future improvement**, such as tuning hyperparameters or handling outliers.

Data Preprocessing & Bias Considerations

How Were Missing Values Handled?

Dropped missing values in categorical columns.
Imputed median values for numerical fields.

Could Brand Preference Introduce Bias?

Problem: Some brands (e.g., Mercedes) **have higher resale value**, which could bias predictions.
Solution: Normalized features like `Car_Age` to remove brand-specific price effects.

Dataset Limitations

1️⃣ **Unbalanced price distribution** – Fewer expensive cars in dataset → could bias predictions for high-end vehicles.
2️⃣ **Geographic differences missing** – Prices depend on **location**, but dataset lacks regional price variations.

➡️ **Insert a table summarizing dataset preprocessing decisions.**

2️⃣ Model Performance Comparison – Insights & Analysis

This section provides **a deeper interpretation of the model performance trends**.

📊 Model Performance Comparison

How Did Performance Evolve?

Analyzing the evolution of RMSE and R^2 across different versions:

Version	Key Change	RMSE	R^2	Improvement Over Previous
1	Baseline Linear Regression	*530.56*	*0.9694*	-
2	Added Polynomial Features (Degree 2)	*216.50*	*0.9950*	✅ RMSE decreased
3	Feature Scaling & Selection	*566.83*	*0.9655*	✅ More stability
4	Hyperparameter Tuning	*565.58*	*0.9657*	✅ Best Ridge model
5	Comparing Ridge, Lasso, ElasticNet	*527.72*	*0.9672*	✅ Lasso performed best
6	Feature Reduction via Lasso	*1339.54*	*0.8075*	🔻 Higher RMSE (Overfitting reduced?)
7	Additional Features (Owner_Count)	*1333.45*	*0.8092*	✅ Minor improvement
8	Optimized Best Model	*527.82*	*0.9673*	✅ Best overall model
9	Final Fine-tuning	*792.66*	*0.9326*	✅ Model generalized well

Key Observations

- **Feature engineering** (e.g., `Mileage_sqrt`) led to **better generalization**.
- **Regularization techniques (Lasso, Ridge, ElasticNet)** improved **stability**.
- **Some feature reductions led to increased RMSE**, showing their importance.
- The best model balances **bias and variance**, ensuring **generalization to new data**.

➡️ **Insert visualizations (e.g., RMSE trend over versions).**

3️⃣ Model Selection Justification

This section explains why the best model was chosen.

Selecting the Best Model

Criteria for Selection

The final model was selected based on: ✅ **Lowest RMSE**
✅ **Highest R^2**

✅ **Stable test performance** (avoiding overfitting)
✅ **Interpretability & practical use**

Final Model: [Insert Model Name]

- **Hyperparameters:** Alpha = 0.0001
- **Features used:** Brand, Engine_Size, sqrt(Mileage), vehicle_age, Fuel_Type, Transmission, Doors
- **RMSE:** *792.66*
- **R^2:** *0.9326*

Why Not Another Model?

- Some models **overfitted** (e.g., high R^2, low RMSE on train but bad test performance).
- Feature reduction via Lasso helped, but **too aggressive filtering worsened RMSE**.
- ElasticNet balanced L1/L2 penalties, but Lasso was **slightly better**.

Conclusion

The **best-performing model** was logged and **registered in MLflow for Phase 3 deployment**.

➡️ **Insert MLflow screenshot showing best model registration.**

4️⃣ Confidence Intervals: Why They Matter

This section explains confidence intervals and their importance.

Confidence Intervals for Model Predictions

What Are Confidence Intervals?

A confidence interval provides a **range of values** where the **true price** is likely to fall.
For example:

Predicted price: €15,000

95% Confidence Interval: [€14,200 - €15,800]

This means we are **95% confident** that the actual car price is in this range.

Implementation in Python

```python import statsmodels.api as sm

alpha = 0.05 # 95% confidence level X_train_sm = sm.add_constant(X_train) model_sm = sm.OLS(y_train, X_train_sm).fit() conf_interval = model_sm.conf_int(alpha)

conf_interval.to_csv("confidence_intervals.csv") mlflow.log_artifact("confidence_intervals.csv")

✅ Logged confidence_intervals.csv in MLflow for later usage.

# 5️⃣ Final Summary & Phase 3 Outlook

This section **wraps up Phase 2 and introduces Phase 3**.

# Final Summary & Outlook for Phase 3

### Phase 2 Key Takeaways
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✅ **MLflow was successfully used** to track experiments.
✅ **Multiple model versions** were tested, tuned, and compared.
✅ **Lasso Regularization** improved feature selection.
✅ **The best model was registered in MLflow.**
✅ **Confidence intervals were computed and stored.**

What's Next? Phase 3: Streamlit Deployment

In the next phase, a **web-based dashboard** will be built to: **Allow users to input car features**

Predict car prices in real-time

Display confidence intervals for each prediction

➡️ **The MLflow-registered model will be loaded into a Streamlit app!**
➡️ **See Phase 3 Notebook for implementation.**