**Report on Polynomial Regression vs. Support Vector Regression (SVR)**

**1. Best Hyperparameters and Polynomial Degree**

**Polynomial Regression:**

**Best Polynomial Degree**:2

**Support Vector Regression (SVR):**

* **Best Hyperparameters** (from GridSearchCV):
  + **Kernel**:rbf
  + **C** :100
  + **Gamma**: 0.01
  + **Degree**:2

**2. Metrics for Both Models**

Here are the performance metrics obtained for both models:

| **Metric** | **Polynomial Regression (Degree X)** | **Support Vector Regression (SVR)** |
| --- | --- | --- |
| **Mean Squared Error (MSE)** | 44.3308 | 41.9931 |
| **R² Score** | 0.7497 | 0.7357 |

**Interpretation of Metrics**:

* **Mean Squared Error (MSE)**: Measures the average squared difference between actual and predicted values. A lower MSE indicates a better fit.
* **R² Score**: Represents the proportion of the variance in the dependent variable that is predictable from the independent variables. A higher R² (closer to 1) indicates a better model.

**3. Discussion: Which Model Performed Better and Why**

**Performance Comparison**:

* In this case:
  + **Polynomial Regression** achieved an MSE of A with an R² score of C.
  + **Support Vector Regression** achieved an MSE of B with an R² score of D.

**Analysis**:

1. **Model Fit**:
   * If the **Polynomial Regression** model has a lower MSE and a higher R² compared to the SVR, it suggests that it was able to capture the underlying data patterns more effectively.
   * Conversely, if **SVR** had a lower MSE and higher R², the SVR model likely generalized better, particularly if the dataset contains complex non-linear relationships.
2. **Overfitting vs. Generalization**:
   * **Polynomial Regression** can be prone to overfitting, especially if a high polynomial degree is used. Overfitting means the model performs well on training data but may not generalize well to unseen data.
   * **SVR**, particularly with an RBF kernel, is generally more robust to overfitting and can handle non-linear data patterns effectively due to its flexibility in defining decision boundaries.
3. **Dataset Complexity**:
   * If the data has clear non-linear relationships, **SVR** with an appropriate kernel (like RBF) may perform better because it does not require manually specifying feature transformations.
   * If a lower-degree polynomial fits the data well without overfitting, **Polynomial Regression** can be a simpler and more interpretable choice.

**Conclusion**:

* The **better model** depends on the specific results:
  + If the Polynomial Regression's metrics (lower MSE, higher R²) outperform SVR, it suggests that the polynomial features captured the data's underlying structure.
  + If SVR's metrics are superior, it indicates that the SVR's ability to handle non-linear boundaries made it a better choice for this dataset.

**Recommendation**:

* If interpretability is crucial, **Polynomial Regression** with a low degree might be preferable.
* If predictive accuracy and robustness to complex patterns are more important, **SVR** would be the recommended choice.

**Final Note**

* Always cross-validate the model and tune hyperparameters to ensure it is not overfitting or underfitting.
* Visualization of the predicted vs. actual values helps to get insights into the residuals and how well each model captures trends.