**Advantages of Support Vector Machines (SVMs) over Regular Regression models**:

1. Non-linearity handling: SVMs can effectively handle non-linear relationships between features and the target variable by using different kernel functions (e.g., linear, polynomial, radial basis function). This allows SVMs to capture complex patterns in the data, which regular regression models may struggle with.

2. Robustness to overfitting: SVMs aim to maximize the margin between classes, which often leads to better generalization and robustness against overfitting, especially in high-dimensional spaces. Regular regression models might overfit if the complexity of the model is not appropriately controlled.

3. Outlier resistance: SVMs are less sensitive to outliers compared to some traditional regression models. The use of the margin helps in focusing on support vectors, which are the critical data points for defining the decision boundary, thus reducing the impact of outliers.

4. Versatility in kernel selection: SVMs offer various kernel functions that can map data into higher-dimensional spaces, allowing better separation of classes. This flexibility provides more options to model complex relationships compared to linear regression or traditional regression models.

5. Effective in high-dimensional spaces: SVMs perform well even in cases where the number of dimensions (features) is greater than the number of samples, which is a scenario where regular regression models might struggle due to the "curse of dimensionality."

6. Handles both classification and regression: While regular regression models are designed primarily for regression tasks, SVMs can be adapted for both classification and regression problems.

7. Control over trade-off between bias and variance: SVMs provide control over the trade-off between bias and variance through tuning the regularization parameter (C) and the choice of kernel. This allows practitioners to adjust the model's complexity according to the problem at hand.