

QA from GPT

Lecture 7 - SVM hard margin

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0. What is SVM? Why is it so popular?

Support Vector Machine (SVM) is a powerful, versatile supervised machine learning algorithm used for both classification and regression tasks. It is particularly well-suited for classification of complex but small- or medium-sized datasets. Here's an overview of what SVM is and why it has gained popularity in various fields:

What is SVM?

1. **Fundamental Concept**: At its core, SVM aims to find the optimal hyperplane (in two-dimensional space, this would be a line) that best separates the data points into different classes. In higher-dimensional space, this hyperplane could be a plane or a multidimensional surface.
2. **Support Vectors**: These are the data points nearest to the hyperplane, which influence the position and orientation of the hyperplane. The SVM uses these points to maximize the margin between the classes.
3. **Maximizing the Margin**: The margin is the distance between the hyperplane and the nearest data point from either class. Maximizing this margin helps in reducing generalization error.
4. **Handling Non-Linearly Separable Data**: For datasets that are not linearly separable, SVM uses the kernel trick. This trick involves mapping the input features into a higher-dimensional space where a hyperplane can be used to separate the data.
5. **Regression and Outlier Detection**: Beyond classification, SVM can be adapted for regression (Support Vector Regression or SVR) and outlier detection, showcasing its flexibility.

Why is SVM Popular?

1. **Effectiveness in High-Dimensional Spaces**: SVM works well in high-dimensional spaces, making it suitable for applications with many features, like text and image classification.
2. **Versatility**: The choice of the kernel function allows SVM to be adaptable to a wide variety of data types and structures, enhancing its applicability to different domains.

3. ****Generalization****: Due to the emphasis on maximizing the margin, SVM tends to generalize well, making it robust against overfitting, especially in cases where the number of dimensions exceeds the number of samples.
4. ****Sparse Data****: SVM is effective in cases where the data is sparse, which is common in fields like text analysis.
5. ****Clear Margin of Separation****: SVM's focus on creating a clear margin of separation provides a more definitive decision boundary compared to some other classifiers.
6. ****Theoretical Foundations****: SVM is grounded in the principles of statistical learning theory and structural risk minimization, providing a strong theoretical foundation that contributes to its robustness and efficacy.
7. ****Wide Range of Applications****: Its ability to handle various types of data and problems makes SVM popular across different fields, including image recognition, bioinformatics, pattern recognition, and text categorization.

In summary, SVM's popularity stems from its versatility, effectiveness in high-dimensional spaces, and robustness in terms of generalization, making it a go-to algorithm for many machine learning practitioners and researchers in diverse fields.

1. What is Hyperplanes and Decision Boundaries in a SVM problem?

In the context of Support Vector Machines (SVM), the concepts of hyperplanes and decision boundaries are central to understanding how the algorithm works to classify data.

Hyperplanes:

A hyperplane is a flat affine subspace whose dimension is one less than that of the ambient space. For example, in a two-dimensional space (like a plane), a hyperplane is a line, and in a three-dimensional space, it is a plane. In higher dimensions, we still refer to it as a hyperplane, even though we cannot visualize it.

In SVM, a hyperplane is used to separate data points belonging to different classes. The goal of SVM is to find the optimal hyperplane that best separates the data points into their respective categories.

- ****Optimal Hyperplane****: The optimal hyperplane is the one that has the maximum margin, which is the maximum distance between data points of both classes. Maximizing the margin provides some reinforcement so that future data points can be classified with

more confidence.

Decision Boundaries:

The decision boundary is the region in feature space that separates different classes. In the case of SVM, the decision boundary is determined by the hyperplane. Points on one side of the hyperplane are classified into one category, while points on the other side are classified into another.

- **Support Vectors**: The decision boundary is influenced by particular data points that are closest to the hyperplane, known as support vectors. These support vectors are critical, as their removal can alter the position of the decision boundary. SVMs are named after these points because they "support" the creation of the decision boundary.

- **Linear vs Non-linear Boundaries**: If the data is linearly separable, SVM will find a linear decision boundary (a straight line in two dimensions, or a hyperplane in higher dimensions). When data is not linearly separable, SVM can use a kernel function to map the input space into a higher-dimensional space where a linear separation is possible. This is where the concept of decision boundaries becomes more abstract, as the separation in the high-dimensional space corresponds to a non-linear boundary in the original input space.

Understanding hyperplanes and decision boundaries is crucial for interpreting how SVM models make classifications. By finding the optimal hyperplane, SVM ensures that new, unseen data points can be classified with a high degree of confidence based on their position relative to this boundary in the feature space.

2. What are the margins in SVM?

In the context of Support Vector Machines (SVM), the concept of margins is crucial and central to its classification strategy. Margins refer to the distance between the separating hyperplane (decision boundary) and the closest data points from each class. These closest points are known as **support vectors**. SVM aims to maximize this margin to improve the model's generalization ability. Here's a breakdown of the concept:

Hard Margin SVM (Linearly Separable Case)

- **Hard Margin**: In scenarios where data is linearly separable, SVM finds a hyperplane that perfectly separates the classes while maximizing the distance between the hyperplane and the nearest data point from each class. This distance is the "hard margin."

- **Support Vectors**: These are the data points that lie closest to the hyperplane and influence its orientation and position. They are pivotal because if these points shift, the position of the hyperplane will also change.

- **Maximizing the Margin**: By maximizing this margin, SVM aims to increase the model's robustness and its ability to generalize well to unseen data, reducing the risk of overfitting.

Soft Margin SVM (Non-Linearly Separable Case)

- **Soft Margin**: When data is not linearly separable, enforcing a hard margin can lead to overfitting. In such cases, SVM introduces a "soft margin" approach, allowing some data points to be misclassified or to fall within the margin if it leads to a better overall model.
- **Regularization Parameter (C)**: This parameter controls the trade-off between maximizing the margin and minimizing the classification error. A higher value of C tries to classify all training examples correctly (a narrower margin), while a lower value of C allows more misclassifications (a wider margin), aiming for better generalization.

Margins in Non-Linear SVM

- When dealing with non-linear data, SVM employs the kernel trick to map input features into a higher-dimensional space where a linear separation is possible. Even in this transformed space, the concept of maximizing the margin remains the same, although the margin and hyperplane are in the transformed feature space, not in the original input space.

Importance of Margins

- **Generalization**: A larger margin reduces the model's complexity, leading to better generalization on unseen data.
- **Robustness**: The margin acts as a buffer zone that helps the model remain robust to small changes in the input data.

Understanding margins is essential for comprehending how SVM works and why it is effective, especially in scenarios where maximizing the distance between different classes can lead to better classification performance and model generalization.

3. How to define the objective function of SVM with a hard margin?

The objective function of an SVM with a hard margin is designed to find the optimal hyperplane that separates two classes while maximizing the margin between them. This margin is the distance between the hyperplane and the closest points from either class, known as support vectors. For a hard margin SVM, we assume that the data is linearly separable, meaning there exists at least one hyperplane that can perfectly separate the two classes without any misclassification.

Here's how the objective function and the constraints are defined in the context of a binary classification problem:

Objective Function

The goal is to maximize the margin between the two classes. The margin is inversely proportional to the norm of the weight vector \mathbf{w} . Thus, minimizing $\frac{1}{2} \|\mathbf{w}\|^2$ (where $\|\mathbf{w}\|^2 = \mathbf{w}^T \mathbf{w}$) maximizes the margin. The factor of $\frac{1}{2}$ is used for mathematical convenience (it simplifies the derivative when optimizing the function).

So, the objective function is:

$$\min_{\mathbf{w}, b} \frac{1}{2} \|\mathbf{w}\|^2$$

Constraints

For each data point (\mathbf{x}_i, y_i) where \mathbf{x}_i is the feature vector and y_i is the class label (typically $+1$ or -1), the following constraints must hold:

$$y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1, \quad \text{for } i = 1, 2, \dots, N$$

These constraints ensure that all data points are correctly classified with a margin at least 1. Here, \mathbf{w} is the normal vector to the hyperplane, and b is the bias term.

Optimization Problem

The SVM training involves solving this optimization problem, where we minimize $\frac{1}{2} \|\mathbf{w}\|^2$ subject to the constraints $y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1$ for all i . This problem is typically solved using quadratic programming methods.

The solution to this optimization problem gives us the values of \mathbf{w} and b that define the optimal hyperplane. The support vectors are the data points that lie closest to the hyperplane, and they are the critical elements that influence the position and orientation of the hyperplane.

In summary, the objective function of an SVM with a hard margin aims to maximize the margin between the classes by minimizing the norm of the weight vector while ensuring that all data points are classified correctly with a margin of at least 1.

4. Why The margin is inversely proportional to the norm of the weight vector $\|\mathbf{w}\|$? Can you derive it?



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The objective function of SVM with a hard margin is designed to find the optimal hyperplane that separates the data points into two classes while maximizing the margin between these classes. To understand why the margin is inversely proportional to the norm of the weight vector \mathbf{w} , we need to delve into the mathematics of SVM.

Mathematical Derivation:

1. **Equation of the Hyperplane:** The hyperplane in an SVM is defined by the equation $\mathbf{w} \cdot \mathbf{x} + b = 0$, where \mathbf{w} is the weight vector, \mathbf{x} is the input vector, and b is the bias.
2. **Distance from a Point to the Hyperplane:** The distance d from any point \mathbf{x}_i to the hyperplane is given by the formula:

$$d(\mathbf{x}_i) = \frac{|\mathbf{w} \cdot \mathbf{x}_i + b|}{\|\mathbf{w}\|}.$$

This equation comes from the geometric distance between a point and a plane.

3. **Margin Definition:** The margin M is defined as the distance between the closest points of the two classes (support vectors) to the hyperplane. For the support vectors, the equations $\mathbf{w} \cdot \mathbf{x}_+ + b = 1$ and $\mathbf{w} \cdot \mathbf{x}_- + b = -1$ hold, where \mathbf{x}_+ and \mathbf{x}_- are support vectors from the positive and negative classes, respectively.
3. **Margin Definition:** The margin M is defined as the distance between the closest points of the two classes (support vectors) to the hyperplane. For the support vectors, the equations $\mathbf{w} \cdot \mathbf{x}_+ + b = 1$ and $\mathbf{w} \cdot \mathbf{x}_- + b = -1$ hold, where \mathbf{x}_+ and \mathbf{x}_- are support vectors from the positive and negative classes, respectively.
4. **Calculating the Margin:** The margin is twice the distance from the hyperplane to the nearest point (any support vector), so using the distance formula:

$$M = d(\mathbf{x}_+) + d(\mathbf{x}_-) = \frac{2}{\|\mathbf{w}\|}.$$

This is because for the support vector \mathbf{x}_+ , $\mathbf{w} \cdot \mathbf{x}_+ + b = 1$, and for \mathbf{x}_- , $\mathbf{w} \cdot \mathbf{x}_- + b = -1$. When you plug these into the distance formula and simplify, you get $M = \frac{2}{\|\mathbf{w}\|}$.

Objective Function for Hard Margin SVM:

With the understanding that we want to maximize the margin M which is $\frac{2}{\|\mathbf{w}\|}$, maximizing M is equivalent to minimizing $\|\mathbf{w}\|$ or minimizing $\frac{1}{2} \|\mathbf{w}\|^2$ (squared norm is often used for computational convenience and differentiability).

Hence, the objective function for hard margin SVM can be stated as:

- Minimize: $\frac{1}{2} \|\mathbf{w}\|^2$
- Subject to: $y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1$ for all i .

This formulation ensures that all data points are correctly classified (for a perfectly separable dataset) while maximizing the margin, thereby achieving the best generalization performance.

5. What is Lagrangian method in optimization?

The Lagrangian method in optimization is a powerful strategy used to find the maximum or minimum of a function subject to constraints. It's particularly useful in situations where direct optimization is challenging due to these constraints. Here's an overview of how the method works:

Fundamentals of the Lagrangian Method:

1. **Objective Function:** You start with an objective function $f(x, y, \dots)$ that you want to maximize or minimize.
2. **Constraints:** You have one or more constraints on the solution, expressed as equations. For example, a constraint might be $g(x, y, \dots) = 0$.
3. **Lagrangian Function:** You construct the Lagrangian function, which incorporates the objective function and the constraints. Each constraint is multiplied by a corresponding Lagrange multiplier (a new variable). For a single constraint, the Lagrangian \mathcal{L} is:

$$\mathcal{L}(x, y, \dots, \lambda) = f(x, y, \dots) - \lambda(g(x, y, \dots) - c)$$

where λ is the Lagrange multiplier, and c is the value to which the constraint function g is set (often zero).

How It Works:

- **Critical Points:** You find the critical points of the Lagrangian function by taking its derivatives with respect to all variables, including the original variables and the Lagrange multipliers, and setting them to zero. This step involves solving a system of equations.
- **Solving for Variables:** Solve the system of equations to find the values of the variables and the Lagrange multipliers.
- **Interpretation:** The solutions give you the points at which the objective function is optimized, subject to the constraints.

Multiple Constraints:

For multiple constraints, the Lagrangian is extended by adding a term for each constraint, each with its own Lagrange multiplier:

$$\mathcal{L}(x, y, \dots, \lambda_1, \lambda_2, \dots) = f(x, y, \dots) - \lambda_1(g_1(x, y, \dots) - c_1) - \lambda_2(g_2(x, y, \dots) - c_2) - \dots$$

Applications:

- **Economics:** Used in optimization problems, like maximizing utility or profit under certain constraints.
- **Engineering:** Applied in design optimization to achieve the best performance under

physical or technical constraints.

- ****Machine Learning****: The Lagrangian method is fundamental in formulating solutions for various algorithms, including SVM, where it's used to optimize the objective function subject to constraints.

The Lagrangian method is a cornerstone of optimization theory, providing a systematic approach to tackling constrained optimization problems across numerous fields.

6. What are KKT conditions?

The **Karush-Kuhn-Tucker (KKT) conditions** are a set of requirements that provide necessary and sufficient conditions for a solution to be optimal in a constrained optimization problem, particularly in nonlinear programming. These conditions generalize the method of Lagrange multipliers to handle inequality constraints.

Here's a breakdown of the KKT conditions, typically applied in the context of an optimization problem that aims to minimize a function $f(x)$ subject to equality constraints $h_i(x) = 0$ and inequality constraints $g_j(x) \leq 0$:

1. **Stationarity**: This condition extends the idea of setting the gradient of the Lagrangian to zero in the unconstrained or equality-constrained scenario. It ensures that the gradient of the objective function is a linear combination of the gradients of the constraints:

$$\nabla f(x) - \sum_i \lambda_i \nabla h_i(x) - \sum_j \mu_j \nabla g_j(x) = 0,$$

where λ_i and μ_j are the Lagrange multipliers for the equality and inequality constraints, respectively.

2. **Primal Feasibility**: The solution must adhere to the original constraints of the problem:

$$\begin{aligned} h_i(x) &= 0 && \text{for all } i, \\ g_j(x) &\leq 0 && \text{for all } j. \end{aligned}$$

3. **Dual Feasibility**: This condition ensures that the Lagrange multipliers associated with the inequality constraints are non-negative:

$$\mu_j \geq 0 \quad \text{for all } j.$$

4. **Complementary Slackness**: This condition links the inequality constraints and their corresponding Lagrange multipliers. If an inequality constraint is strictly greater than its bound (not active), then its multiplier should be zero. Conversely, if the multiplier is positive, the constraint should be active (the inequality holds as an equality):

$$\mu_j g_j(x) = 0 \quad \text{for all } j.$$

In the context of SVM (Support Vector Machine), the KKT conditions are crucial for determining the optimal margin and support vectors. During SVM training, especially in the dual formulation, the KKT conditions help identify the support vectors (data points that lie on or violate the margin). These conditions ensure that the solution not only adheres to the constraints (the data points are correctly classified or within the margin for soft-margin SVM) but also maximizes the margin between the two classes.

7. How to use quadratic programming in Linear Quadratic Solver to solve a constrained optimization problem?

Quadratic programming (QP) is a type of optimization problem where the objective function is quadratic, and the constraints are linear. It's commonly used in various fields, including finance, machine learning, and operations research. The general form of a quadratic programming problem is:

Minimize:

$$f(x) = \frac{1}{2}x^T Qx + c^T x$$

Subject to:

$$Ax \leq b$$

$$Ex = d$$

Here, x is the vector of decision variables, Q is a symmetric matrix representing the quadratic part of the objective function, c is a vector representing the linear part of the objective function, A and b represent the coefficients and constants of the inequality constraints, and E and d represent the coefficients and constants of the equality constraints.

Using a Linear Quadratic Solver:

1. **Define the Problem**: Clearly specify the objective function and constraints. The objective should be in the quadratic form, and constraints should be linear.
2. **Formulate the Matrices**: Express the problem in matrix form to fit the solver's input requirements. You'll need to define the matrices Q , c , A , b , E , and d .
3. **Choose a Solver**: Select a software or library that provides quadratic programming capabilities. Common choices include CVXOPT in Python, MATLAB's Optimization Toolbox, or solvers like CPLEX and Gurobi.
4. **Implement the Solver**:
 - Input the matrices into the solver. This step varies depending on the specific software or library you're using.

- Execute the solver to find the optimal values of $\|x\|$ that minimize the objective function while satisfying the constraints.

5. **Interpret the Results**: Analyze the output from the solver, which typically includes the optimal value of $\|x\|$ and the minimum value of the objective function. Ensure that the solution satisfies the constraints.

Example in Python with CVXOPT:

Let's consider a simple example where you have an objective function $f(x) = \frac{1}{2} x^T Q x + c^T x$ and some linear constraints $Ax \leq b$. Here's how you might set this up using the CVXOPT library in Python:

```
python
import cvxopt

# Define the matrices
Q = cvxopt.matrix([[2.0, 0.0], [0.0, 2.0]]) # For  $x^2 + y^2$ 
c = cvxopt.matrix([0.0, 0.0])
A = cvxopt.matrix([[1.0, -1.0], [-1.0, -2.0], [-1.0, 0.0], [0.0, -1.0]]) # Constraints coefficients
b = cvxopt.matrix([1.0, -2.0, 0.0, 0.0]) # Constraints constants

# Solve the problem
solution = cvxopt.solvers.qp(Q, c, A, b)

# Extract the solution
x_optimal = solution['x']
```

In this example, `cvxopt.solvers.qp` is used to solve the quadratic programming problem. The matrices Q , c , A , and b are defined according to the problem's specifications, and the solution provides the optimal values for x .

Quadratic programming is a powerful tool for solving optimization problems with a quadratic objective function and linear constraints, widely applicable across different domains.

8. Take an example of SVM applications in biomedical field

One intriguing application of Support Vector Machines (SVM) in the biomedical field is in the area of cancer diagnosis and prognosis. Let's explore how SVM can be utilized for breast cancer detection and classification, which serves as a concrete example of its

application in biomedical research.

Example: Breast Cancer Detection and Classification

****Problem Definition****: The challenge is to accurately classify tumors as benign (non-cancerous) or malignant (cancerous) based on features extracted from breast mass images.

1. Data Collection and Feature Extraction:

- ****Data Source****: The data could come from a repository like the Wisconsin Breast Cancer Dataset (WBCD), which contains features extracted from digitized images of fine needle aspirate (FNA) of breast masses.
- ****Features****: These features might include characteristics of cell nuclei present in the images, such as texture, shape, size, smoothness, and symmetry.

2. Preprocessing:

- ****Normalization****: The features are normalized to ensure that no single feature dominates the classification due to its scale.
- ****Training and Test Split****: The dataset is divided into training and test sets to evaluate the model's performance.

3. SVM Model Training:

- ****Kernel Selection****: A kernel is chosen to transform the data. In cases where the data is not linearly separable, the Radial Basis Function (RBF) kernel is a common choice.
- ****Training****: The SVM model is trained on the training set. It learns to classify the samples by finding the hyperplane that best separates the benign from malignant samples with the maximum margin.

4. Model Evaluation:

- ****Validation****: The model is validated using the test set to assess its accuracy, sensitivity (true positive rate), and specificity (true negative rate).
- ****Cross-Validation****: Techniques like k-fold cross-validation can be employed to ensure the model's robustness and avoid overfitting.

5. Clinical Application:

- ****Diagnostic Tool****: Once validated, the SVM model can be used as a diagnostic tool to assist healthcare professionals in classifying breast tumors, aiding in early and accurate diagnosis.
- ****Prognostic Tool****: Beyond diagnosis, SVM can also be utilized for prognosis, predicting the likelihood of recurrence or the aggressiveness of the tumor based on its characteristics.

Benefits in the Biomedical Field:

- ****Accuracy****: SVM's ability to handle high-dimensional data makes it well-suited for

biomedical applications where datasets often have many features.

- **Generalization**: The emphasis on maximizing the margin helps in building models that generalize well to unseen data, which is crucial in medical applications where the cost of misclassification can be high.
- **Interdisciplinary Collaboration**: This application of SVM fosters collaboration between machine learning experts and healthcare professionals, leading to advancements in medical diagnostics and personalized medicine.

In summary, SVM's application in breast cancer detection exemplifies its potential in the biomedical field, offering a powerful tool for improving diagnostic accuracy and patient outcomes. This approach can be adapted to various other medical domains, demonstrating the versatility and impact of SVM in healthcare.

9. Why SVM is mostly used in classification tasks? How to use SVM in regression tasks?

Support Vector Machine (SVM) is predominantly used in classification tasks due to its ability to find the optimal hyperplane that best separates different classes in a feature space. Its effectiveness in classification, especially in high-dimensional spaces and with clear margin separation, has made it a popular choice. However, SVM is not limited to classification; it can be adapted for regression tasks through a method known as Support Vector Regression (SVR).

Why SVM is Popular in Classification Tasks:

1. **Optimal Hyperplane**: SVM is designed to find the hyperplane that maximizes the margin between classes, providing a clear and definitive decision boundary, which is crucial for classification.
2. **Support Vectors**: The algorithm focuses on the data points that are closest to the decision boundary (support vectors), making it efficient and effective even in complex datasets.
3. **Kernel Trick**: The ability to use kernel functions allows SVM to handle non-linearly separable data, broadening its applicability in classification tasks across various domains.
4. **Robustness**: SVM's emphasis on maximizing the margin makes it less prone to overfitting, enhancing its robustness and generalization capability.

Using SVM for Regression Tasks (Support Vector Regression - SVR):

SVR applies the principles of SVM to regression problems. Instead of trying to find a

hyperplane that separates data points into classes, SVR tries to fit a function that can predict a continuous value for new inputs. Here's how SVR works:

1. **Objective**: In SVR, the objective is to predict a continuous value that is as close as possible to the actual value for each input point. The model tries to fit a function within a threshold (epsilon) of the actual values for the training data.
2. **Epsilon-Tube**: SVR allows some errors while fitting the regression function, within a specified margin called the epsilon-tube. Points that fall within this tube are considered acceptable predictions.
3. **Loss Function**: The loss function in SVR penalizes predictions that fall outside the epsilon-tube, ensuring that the model is as accurate as possible while allowing for some flexibility.
4. **Kernel Trick**: Like in SVM for classification, SVR can use different kernel functions to deal with non-linear data. This makes SVR versatile and capable of handling various types of regression tasks.
5. **Hyperparameters**: Key hyperparameters in SVR include the regularization parameter (C), which determines the trade-off between achieving a low error on the training data and minimizing the model complexity for better generalization, and the epsilon parameter, which defines the width of the no-penalty tube.

In summary, while SVM is renowned for its classification capabilities, its adaptation for regression tasks, known as SVR, leverages similar principles to provide a robust and flexible approach for predicting continuous outcomes, showcasing the versatility of the SVM algorithm in different machine learning tasks.

10. What are the differences of parametric methods and non-parametric methods in modelling? Is SVM parametric?

Parametric and non-parametric methods represent two fundamental approaches to modeling in statistics and machine learning, each with its own set of characteristics and use cases. Here's a breakdown of the differences between the two and where SVM stands:

Parametric Methods:

1. **Fixed Number of Parameters**: Parametric methods assume a specific form for the function or model that relates the input to the output. The model is defined by a finite set of parameters, regardless of the size of the dataset.
2. **Assumptions About Data Distribution**: These methods often assume that the data follows a certain distribution, such as the normal distribution in linear regression.

3. **Model Complexity**: The complexity of the model is fixed, not growing with the size of the data. This can make parametric methods faster and less data-intensive.
4. **Risk of Incorrect Assumptions**: If the assumed model is wrong, parametric methods can lead to poor predictions or inferences.
5. **Examples**: Linear regression, logistic regression, and Gaussian naive Bayes.

Non-Parametric Methods:

1. **Flexible Number of Parameters**: Non-parametric methods do not assume a fixed functional form or distribution for the model. The number of parameters can grow with the data.
2. **Fewer Assumptions**: These methods make fewer assumptions about the data distribution, offering more flexibility to capture the data's structure.
3. **Model Complexity**: The complexity can increase with the amount of data, which can capture more details but also requires more data to avoid overfitting.
4. **Data-Driven**: Non-parametric methods are more influenced by the data and can adapt to its underlying structure, making them more versatile but potentially more data-hungry.
5. **Examples**: Decision trees, k-nearest neighbors, and kernel density estimation.

Is SVM Parametric or Non-Parametric?

- SVM is generally considered a non-parametric method. Although the basic SVM with a linear kernel has a fixed number of parameters, when it comes to SVM with non-linear kernels, the complexity and the number of parameters can grow with the size of the training data. The use of kernel functions allows SVM to adapt to the data's structure without a predefined functional form, aligning more with non-parametric methods' characteristics.

In essence, the distinction between parametric and non-parametric methods lies in their flexibility, assumptions, and how they adapt to the data's inherent structure. SVM's flexibility and adaptability, particularly with its kernel trick, place it in the non-parametric category, providing it with the ability to tackle a wide range of problems effectively.