JOHNS HOPKINS
WHITING SCHOOL of ENGINEERING

Gaussian Processes

Bayes Theorem

- **Bayes' Theorem** describes how to update the **probability of a hypothesis** given new evidence
- Bayesian inference involves using Bayes' Theorem to update the **prior distribution** over some unknown quantity (e.g., model parameters, a function) into a **posterior distribution** given the observed data

$$P(H \mid D) = \frac{P(D \mid H) \cdot P(H)}{P(D)}$$

Where:

- P(H D) is the **posterior probability**: the probability of the hypothesis *H* after observing the data *D*.
- P(D | H) is the **likelihood**: the probability of the data *D* given the hypothesis *H*.
- P(H) is the **prior probability**: the probability of the hypothesis before observing the data.
- P(D) is the **marginal likelihood** (or evidence): the total probability of the data, which normalizes the result.

Johns Hopkins Whiting School of Engineering

Gaussian Process

- A **Gaussian Process** is a non-parametric model that allows us to perform Bayesian inference over functions. GPs extend the ideas of Bayesian inference by moving from simple parameter estimation to the estimation of an entire function.

- In Bayesian regression, the goal is to infer the **posterior distribution** over the unknown function that best explains the data, given some prior belief about what that function might look like. This is where the connection to **Bayes' Theorem** arises.

Naïve Bayes Classifier

- **Naive Bayes Classifier** is a **probabilistic classifier** based on **Bayes' Theorem**

- It assumes **conditional independence** between features, given the class label. This means that each feature contributes independently to the probability of the class, even though this assumption might not hold in reality.

JOHNS HOPKINS

WHITING SCHOOL
of ENGINEERING