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Fundamental Concepts of Generative Machine Learning

Erdem Akagündüz, PhD

Graduate School of Informatics, METU, Türkiye



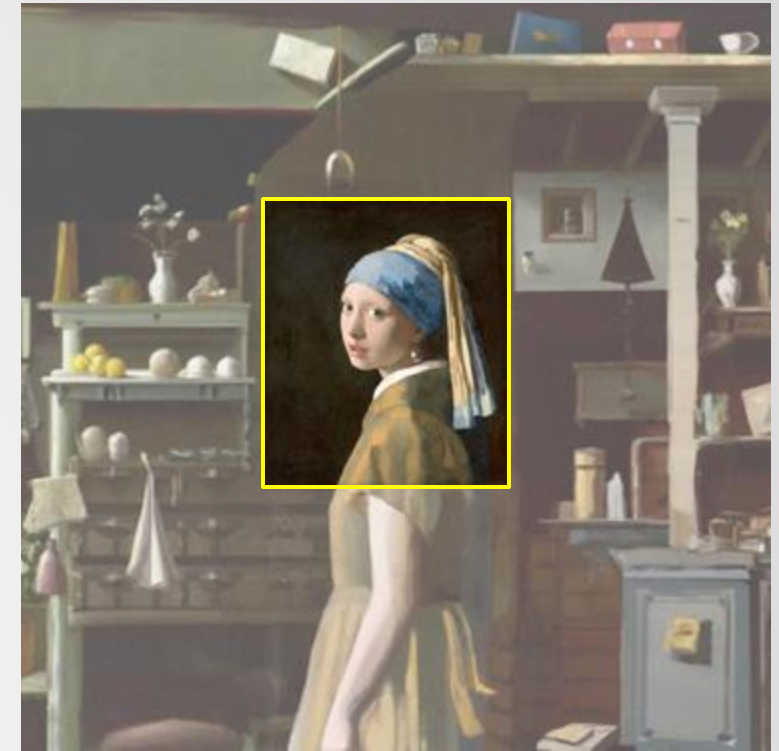
ncc@ulakbim.gov.tr

Lesson 1: Mathematical Background

Welcome to Part I: “Mathematical Background”

This part includes four subsections:

- Generation vs. Discrimination in Machine Learning
- Data Distribution, Sampling, Inference and Generation
- **Expectation and Likelihood**
- Evaluation for Generative Models, Distribution Distances, Divergence and Entropy





Bayes Theorem

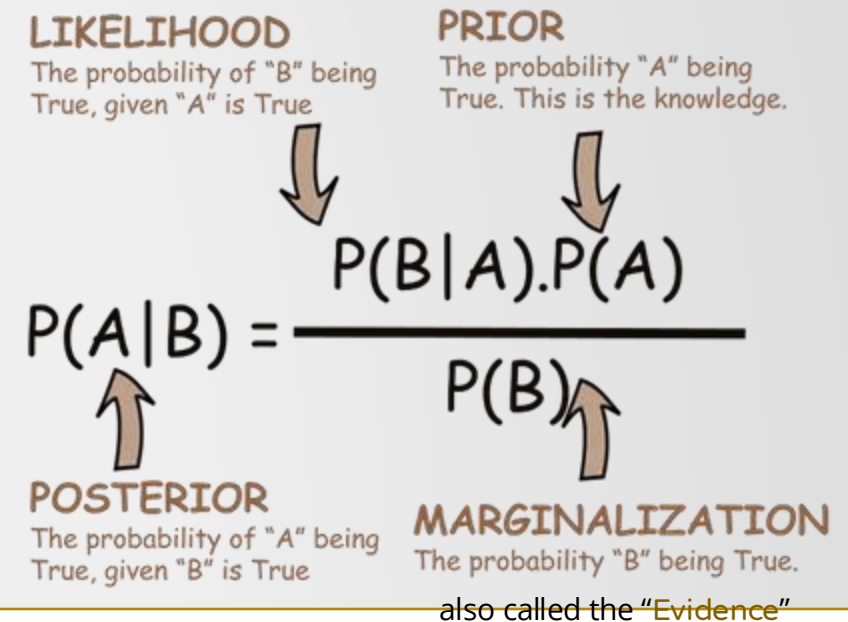
- Bayes' Theorem is a fundamental concept in probability theory that describes the probability of an event based on prior knowledge of related events.
- It provides a way to update our beliefs about the probability of an event as new evidence is obtained.

Independent Events

$$P(X \cap Y) = P(X) \cdot P(Y)$$

Dependent Events

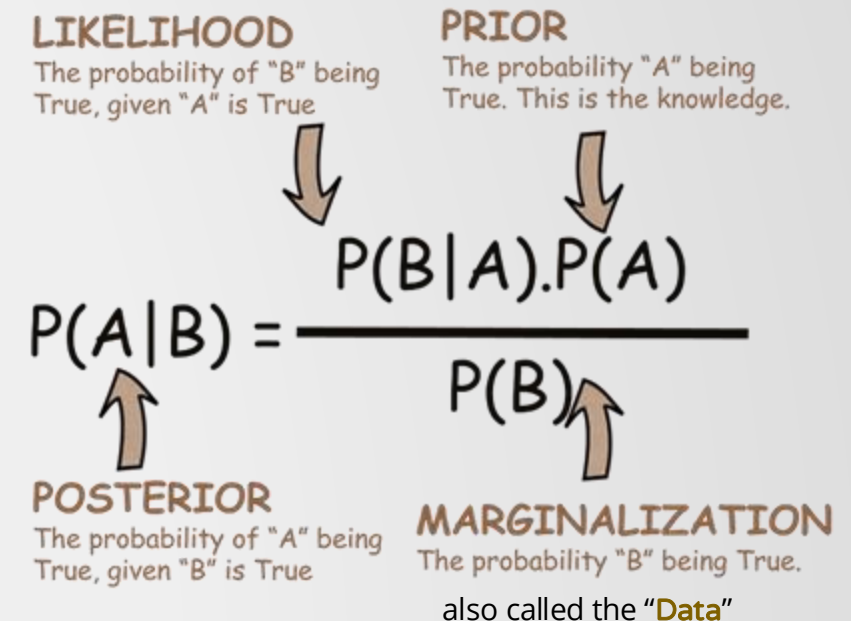
$$P(X \cap Y) = P(Y) \cdot P(X | Y)$$





Bayes Theorem

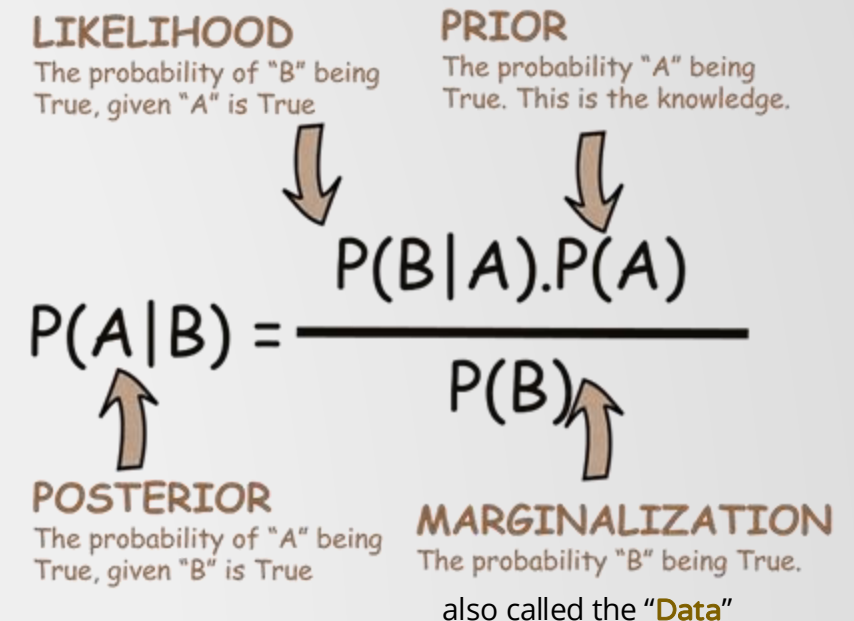
- Bayes Theorem plays a crucial role in generative models, which are used to learn the underlying probability distributions of a given dataset.
- Bayes Theorem provides a way to update our prior beliefs about the parameters of a probability distribution in light of new evidence (i.e., data).
- In the context of generative models, the theorem is used to estimate the parameters of the underlying distribution that generated the data.
- Specifically, it helps us to update our prior beliefs about the parameters of the distribution based on the observed data.





Bayes Theorem

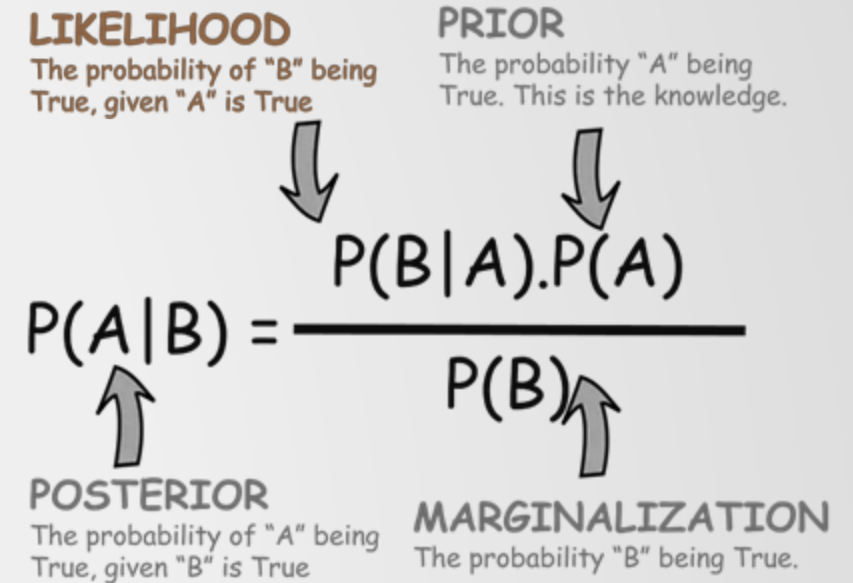
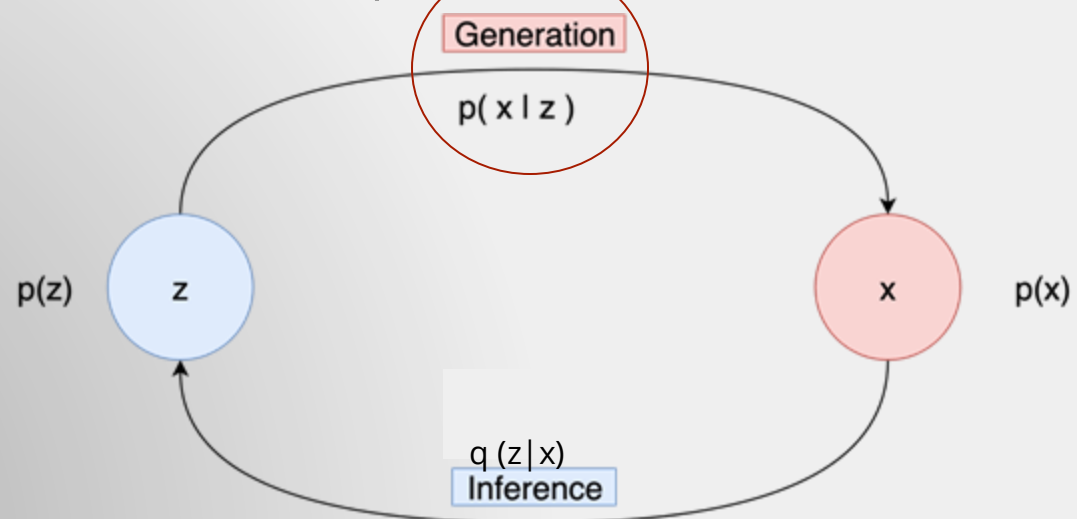
- Bayes Theorem plays a crucial role in generative models, which are used to learn the underlying probability distributions of a given dataset.
- Bayes' Theorem is widely used in deep learning-based generative models, such as GANs, VAEs, and Bayesian neural networks.
- In GANs, for example, the discriminator network can be seen as an approximate likelihood function, and the generator network is used to generate samples from the learned posterior distribution over the latent variables.



Likelihood?

In the context of generative models, the likelihood refers to **the probability of observing a given set of data points under the assumed probability distribution of the generative model.**

In other words, the likelihood measures how well the generative model can explain the observed data.



Maximizing the Likelihood

- Maximizing the likelihood involves finding the set of model parameters θ that maximize the likelihood function (i.e. the Generator)

For example, by using the **log-likelihood loss function** in a deep generative model to maximize the likelihood of the model parameters given the data.

- In deep generative models, the likelihood function is often intractable or difficult to optimize directly.

For example, in VAEs, a lower bound on the likelihood is optimized instead, while in GANs, a game-theoretic objective is used to implicitly maximize the likelihood.

- Maximizing likelihood is a common objective in deep generative models.

Log-likelihood Loss function

- Log-likelihood is a measure of how well a statistical model fits the data it is given. This is commonly used in maximum likelihood estimation (MLE), where the goal is to maximize the likelihood of the observed data. In deep learning, the negative log-likelihood loss is used to train models to minimize the difference between the predicted and actual distributions of the data. The goal is to minimize this difference by adjusting the model's parameters.

```
Docs > torch.nn > NLLLoss
```

NLLLOSS [↗](#)

```
CLASS torch.nn.NLLLoss(weight=None, size_average=None, ignore_index=- 100, reduce=None, reduction='mean') [SOURCE]
```

The negative log likelihood loss. It is useful to train a classification problem with C classes.

If provided, the optional argument `weight` should be a 1D Tensor assigning weight to each of the classes. This is particularly useful when you have an unbalanced training set.

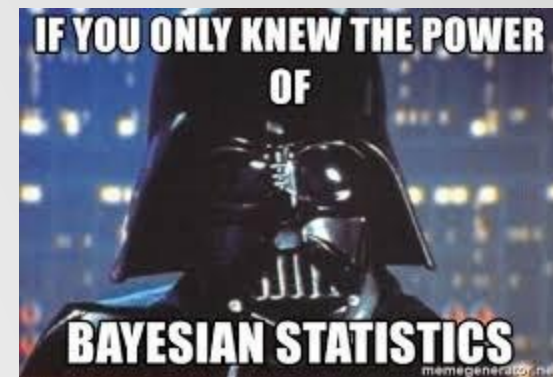
a loss function
the difference
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Next lecture:

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Thanks



This project has received funding from the European High-Performance Computing Joint Undertaking (JU) under grant agreement No 101101903. The JU receives support from the Digital Europe Programme and Germany, Bulgaria, Austria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, Greece, Hungary, Ireland, Italy, Lithuania, Latvia, Poland, Portugal, Romania, Slovenia, Spain, Sweden, France, Netherlands, Belgium, Luxembourg, Slovakia, Norway, Türkiye, Republic of North Macedonia, Iceland, Montenegro, Serbia