Basics of Probabilistic/Bayesian Modeling and Parameter Estimation

Piyush Rai

Topics in Probabilistic Modeling and Inference (CS698X)

Jan 9, 2019

Some Announcements

- Prob-Stats refresher tutorial tomorrow (Thursday, Jan 10), 6:30pm-7:45pm, KD-101

Some Announcements

- Prob-Stats refresher tutorial tomorrow (Thursday, Jan 10), 6:30pm-7:45pm, KD-101
  - Also posted some refresher slides on class webpage (under lecture-1 readings)

Some Announcements

- Prob-Stats refresher tutorial tomorrow (Thursday, Jan 10), 6:30pm-7:45pm, KD-101
  - Also posted some refresher slides on class webpage (under lecture-1 readings)
- A regular class this Saturday, Jan 12 (following Monday schedule)

Some Announcements

- Prob-Stats refresher tutorial tomorrow (Thursday, Jan 10), 6:30pm-7:45pm, KD-101
  - Also posted some refresher slides on class webpage (under lecture-1 readings)
- A regular class this Saturday, Jan 12 (following Monday schedule)
- Sign up on Piazza if you haven't already

Some Announcements

- Prob-Stats refresher tutorial tomorrow (Thursday, Jan 10), 6:30pm-7:45pm, KD-101
  - Also posted some refresher slides on class webpage (under lecture-1 readings)
- A regular class this Saturday, Jan 12 (following Monday schedule)
- Sign up on Piazza if you haven't already
- Regularly watch out for slides, readings etc., on class webpage

Probabilistic Modeling and Inference: The Fundamental Rules

- Keep in mind these two simple rules of probability: sum rule and product rule

$$
\begin{aligned}
P(a) &= \sum_b P(a,b) \quad \text{(Sum Rule)} \\
P(a,b) &= P(a)P(b|a) = P(b)P(a|b) \quad \text{(Product Rule)}
\end{aligned}
$$

Probabilistic Modeling and Inference: The Fundamental Rules

- Keep in mind these two simple rules of probability: sum rule and product rule

$$
\begin{aligned}
P(a) &= \sum_b P(a,b) \quad \text{(Sum Rule)} \\
P(a,b) &= P(a)P(b|a) = P(b)P(a|b) \quad \text{(Product Rule)}
\end{aligned}
$$

- Note: For continuous random variables, sum is replaced by integral: $P(a) = \int P(a,b)db$

Probabilistic Modeling and Inference: The Fundamental Rules

- Keep in mind these two simple rules of probability: sum rule and product rule

$$
\begin{aligned}
P(a) &= \sum_b P(a,b) \quad \text{(Sum Rule)} \\
P(a,b) &= P(a)P(b|a) = P(b)P(a|b) \quad \text{(Product Rule)}
\end{aligned}
$$

- Note: For continuous random variables, sum is replaced by integral: $P(a) = \int P(a,b)db$
- Another rule is the Bayes rule (can be easily obtained from the above two rules)

$$
P(b|a) = \frac{P(b)P(a|b)}{P(a)} = \frac{P(b)P(a|b)}{\int P(a,b)db} = \frac{P(b)P(a|b)}{\int P(b)P(a|b)db}
$$

Probabilistic Modeling and Inference: The Fundamental Rules

- Keep in mind these two simple rules of probability: sum rule and product rule

$$P(a) = \sum_b P(a,b) \quad \text{(Sum Rule)}$$
$$P(a,b) = P(a)P(b|a) = P(b)P(a|b) \quad \text{(Product Rule)}$$

- Note: For continuous random variables, sum is replaced by integral: $P(a) = \int P(a,b)db$
- Another rule is the Bayes rule (can be easily obtained from the above two rules)

$$P(b|a) = \frac{P(b)P(a|b)}{P(a)} = \frac{P(b)P(a|b)}{\int P(a,b)db} = \frac{P(b)P(a|b)}{\int P(b)P(a|b)db}$$

- All of probabilistic modeling and inference is based on consistently applying these two simple rules

Probabilistic Modeling

- Assume data $\mathbf{X} = \{\boldsymbol{x}_n\}_{n=1}^N$ generated from a probability distribution with parameters θ

$$\boldsymbol{x}_n \sim p(\boldsymbol{x}|\theta, m), \quad n = 1, \ldots, N$$

† Hierarchical Implicit Models and Likelihood-Free Variational Inference (Tran et al (NIPS 2017)

Probabilistic Modeling

- Assume data $\mathbf{X} = \{\boldsymbol{x}_n\}_{n=1}^{N}$ generated from a probability distribution with parameters θ

$$\boldsymbol{x}_n \sim p(\boldsymbol{x}|\theta, m), \quad n = 1, \ldots, N$$

- $p(\boldsymbol{x}|\theta, m)$ is also known as the likelihood (a function of the parameters θ)

† Hierarchical Implicit Models and Likelihood-Free Variational Inference (Tran et al (NIPS 2017)

Probabilistic Modeling

- Assume data $\mathbf{X} = \{\boldsymbol{x}_n\}_{n=1}^N$ generated from a probability distribution with parameters θ

$$\boldsymbol{x}_n \sim p(\boldsymbol{x}|\theta, m), \quad n = 1, \ldots, N$$

- $p(\boldsymbol{x}|\theta, m)$ is also known as the likelihood (a function of the parameters θ)
- Assume a prior distribution $p(\theta|m)$ on the parameters θ

† Hierarchical Implicit Models and Likelihood-Free Variational Inference (Tran et al (NIPS 2017)

Probabilistic Modeling

- Assume data $\mathbf{X} = \{\boldsymbol{x}_n\}_{n=1}^N$ generated from a probability distribution with parameters θ

$$\boldsymbol{x}_n \sim p(\boldsymbol{x}|\theta, m), \quad n = 1, \ldots, N$$

- $p(\boldsymbol{x}|\theta, m)$ is also known as the likelihood (a function of the parameters θ)
- Assume a prior distribution $p(\theta|m)$ on the parameters θ
- Note: Here m collectively denotes "all other stuff" about the model

† Hierarchical Implicit Models and Likelihood-Free Variational Inference (Tran et al (NIPS 2017)

Probabilistic Modeling

- Assume data $\mathbf{X} = \{\boldsymbol{x}_n\}_{n=1}^N$ generated from a probability distribution with parameters θ

$$\boldsymbol{x}_n \sim p(\boldsymbol{x}|\theta, m), \quad n = 1, \ldots, N$$

- $p(\boldsymbol{x}|\theta, m)$ is also known as the likelihood (a function of the parameters θ)
- Assume a prior distribution $p(\theta|m)$ on the parameters θ
- Note: Here m collectively denotes "all other stuff" about the model, e.g.,
  - An "index" for the type of model being considered (e.g., "Gaussian", "Student-t", etc)

† Hierarchical Implicit Models and Likelihood-Free Variational Inference (Tran et al (NIPS 2017)

Probabilistic Modeling

- Assume data $\mathbf{X} = \{\boldsymbol{x}_n\}_{n=1}^N$ generated from a probability distribution with parameters θ

$$\boldsymbol{x}_n \sim p(\boldsymbol{x}|\theta, m), \quad n = 1, \dots, N$$

- $p(\boldsymbol{x}|\theta, m)$ is also known as the likelihood (a function of the parameters θ)
- Assume a prior distribution $p(\theta|m)$ on the parameters θ
- Note: Here m collectively denotes "all other stuff" about the model, e.g.,
  - An "index" for the type of model being considered (e.g., "Gaussian", "Student-t", etc)
  - Any other (hyper)parameters of the likelihood/prior

† Hierarchical Implicit Models and Likelihood-Free Variational Inference (Tran et al (NIPS 2017)

Probabilistic Modeling

- Assume data $\mathbf{X} = \{\boldsymbol{x}_n\}_{n=1}^N$ generated from a probability distribution with parameters θ

$$\boldsymbol{x}_n \sim p(\boldsymbol{x}|\theta, m), \quad n = 1, \ldots, N$$

- $p(\boldsymbol{x}|\theta, m)$ is also known as the likelihood (a function of the parameters θ)
- Assume a prior distribution $p(\theta|m)$ on the parameters θ
- Note: Here m collectively denotes "all other stuff" about the model, e.g.,
  - An "index" for the type of model being considered (e.g., "Gaussian", "Student-t", etc)
  - Any other (hyper)parameters of the likelihood/prior
- Note: Usually we will omit the explicit use of m in the notation

† Hierarchical Implicit Models and Likelihood-Free Variational Inference (Tran et al (NIPS 2017)

Probabilistic Modeling

- Assume data $\mathbf{X} = \{\boldsymbol{x}_n\}_{n=1}^N$ generated from a probability distribution with parameters θ

$$\boldsymbol{x}_n \sim p(\boldsymbol{x}|\theta, m), \quad n = 1, \ldots, N$$

- $p(\boldsymbol{x}|\theta, m)$ is also known as the likelihood (a function of the parameters θ)
- Assume a prior distribution $p(\theta|m)$ on the parameters θ
- Note: Here m collectively denotes "all other stuff" about the model, e.g.,
  - An "index" for the type of model being considered (e.g., "Gaussian", "Student-t", etc)
  - Any other (hyper)parameters of the likelihood/prior
- Note: Usually we will omit the explicit use of m in the notation
  - In some situations (e.g., when doing model comparison/selection), we will use it explicitly

† Hierarchical Implicit Models and Likelihood-Free Variational Inference (Tran et al (NIPS 2017)

Probabilistic Modeling

- Assume data $\mathbf{X} = \{\boldsymbol{x}_n\}_{n=1}^N$ generated from a probability distribution with parameters θ

$$\boldsymbol{x}_n \sim p(\boldsymbol{x}|\theta, m), \quad n = 1, \ldots, N$$

- $p(\boldsymbol{x}|\theta, m)$ is also known as the likelihood (a function of the parameters θ)
- Assume a prior distribution $p(\theta|m)$ on the parameters θ
- Note: Here m collectively denotes "all other stuff" about the model, e.g.,
  - An "index" for the type of model being considered (e.g., "Gaussian", "Student-t", etc)
  - Any other (hyper)parameters of the likelihood/prior
- Note: Usually we will omit the explicit use of m in the notation
  - In some situations (e.g., when doing model comparison/selection), we will use it explicitly
- Note: For some models, the likelihood is not defined explicitly using a probability distribution but implicitly via a probabilistic simulation process (more on such implicit probability models[†] later)

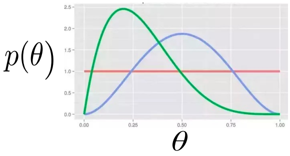
[†] Hierarchical Implicit Models and Likelihood-Free Variational Inference (Tran et al (NIPS 2017)

Probabilistic Modeling

- The prior distribution $p(\theta|m)$ plays a key role in probabilistic (especially Bayesian) modeling

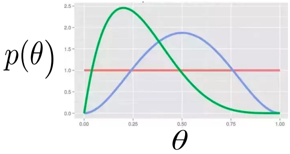
Probabilistic Modeling

- The prior distribution $p(\theta|m)$ plays a key role in probabilistic (especially Bayesian) modeling
  - Reflects our prior beliefs about possible parameter values before seeing the data



Probabilistic Modeling

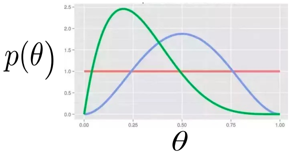
- The prior distribution $p(\theta|m)$ plays a key role in probabilistic (especially Bayesian) modeling
  - Reflects our prior beliefs about possible parameter values before seeing the data



  - Can be "subjective" or "objective" (also a topic of debate, which we won't get into)

Probabilistic Modeling

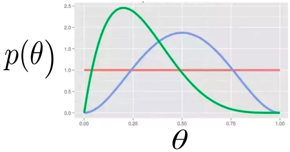
- The prior distribution $p(\theta|m)$ plays a key role in probabilistic (especially Bayesian) modeling
  - Reflects our prior beliefs about possible parameter values before seeing the data



  - Can be "subjective" or "objective" (also a topic of debate, which we won't get into)
  - Subjective: Prior (our beliefs) derived from past experiments
  - Objective: Prior represents "neutral knowledge" (e.g.. uniform, vague prior)

Probabilistic Modeling

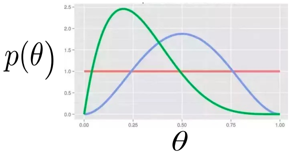
- The prior distribution $p(\theta|m)$ plays a key role in probabilistic (especially Bayesian) modeling
  - Reflects our prior beliefs about possible parameter values before seeing the data



  - Can be "subjective" or "objective" (also a topic of debate, which we won't get into)
  - Subjective: Prior (our beliefs) derived from past experiments
  - Objective: Prior represents "neutral knowledge" (e.g.. uniform, vague prior)
  - Can also be seen as a regularizer (connection with non-probabilistic view)

Probabilistic Modeling

- The prior distribution $p(\theta|m)$ plays a key role in probabilistic (especially Bayesian) modeling
  - Reflects our prior beliefs about possible parameter values before seeing the data

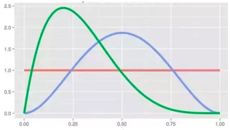


  - Can be "subjective" or "objective" (also a topic of debate, which we won't get into)
  - Subjective: Prior (our beliefs) derived from past experiments
  - Objective: Prior represents "neutral knowledge" (e.g.. uniform, vague prior)
  - Can also be seen as a regularizer (connection with non-probabilistic view)
- The goal of probabilistic modeling is usually one or more of the following

Probabilistic Modeling

- The prior distribution $p(\theta|m)$ plays a key role in probabilistic (especially Bayesian) modeling
  - Reflects our prior beliefs about possible parameter values before seeing the data

$p(\theta)$

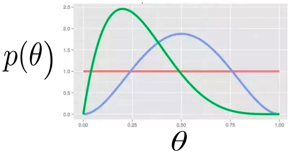


θ

  - Can be "subjective" or "objective" (also a topic of debate, which we won't get into)
  - Subjective: Prior (our beliefs) derived from past experiments
  - Objective: Prior represents "neutral knowledge" (e.g.. uniform, vague prior)
  - Can also be seen as a regularizer (connection with non-probabilistic view)
- The goal of probabilistic modeling is usually one or more of the following
  - Infer the unknowns/parameters θ given data $\mathbf{X}$ (to summarize/understand the data)

Probabilistic Modeling

- The prior distribution $p(\theta|m)$ plays a key role in probabilistic (especially Bayesian) modeling
  - Reflects our prior beliefs about possible parameter values before seeing the data



  - Can be "subjective" or "objective" (also a topic of debate, which we won't get into)
  - Subjective: Prior (our beliefs) derived from past experiments
  - Objective: Prior represents "neutral knowledge" (e.g.. uniform, vague prior)
  - Can also be seen as a regularizer (connection with non-probabilistic view)
- The goal of probabilistic modeling is usually one or more of the following
  - Infer the unknowns/parameters θ given data $\mathbf{X}$ (to summarize/understand the data)
  - Use the inferred quantities to make predictions

Parameter Estimation/Inference

- Can infer the parameters by computing the posterior distribution (Bayesian inference)

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)}$$

Parameter Estimation/Inference

- Can infer the parameters by computing the posterior distribution (Bayesian inference)

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta}$$

Parameter Estimation/Inference

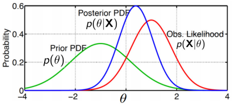
- Can infer the parameters by computing the posterior distribution (Bayesian inference)

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$

Parameter Estimation/Inference

- Can infer the parameters by computing the posterior distribution (Bayesian inference)

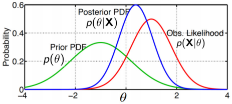
$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$



Parameter Estimation/Inference

- Can infer the parameters by computing the posterior distribution (Bayesian inference)

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$

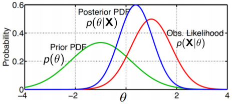


- Note: **Marginal likelihood** $p(\mathbf{X}|m)$ is another very important quantity (more on it later)

Parameter Estimation/Inference

- Can infer the parameters by computing the posterior distribution (Bayesian inference)

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$

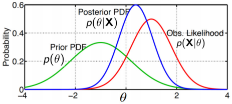


- Note: **Marginal likelihood** $p(\mathbf{X}|m)$ is another very important quantity (more on it later)
- Cheaper alternative: Point Estimation of the parameters.

Parameter Estimation/Inference

- Can infer the parameters by computing the posterior distribution (Bayesian inference)

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$



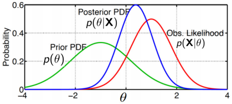
- Note: **Marginal likelihood** $p(\mathbf{X}|m)$ is another very important quantity (more on it later)
- Cheaper alternative: Point Estimation of the parameters. E.g.,
  - **Maximum likelihood estimation (MLE):** Find θ that makes the observed data most probable

$$\hat{\theta}_{ML} = \arg\max_{\theta} \log p(\mathbf{X}|\theta)$$

Parameter Estimation/Inference

- Can infer the parameters by computing the posterior distribution (Bayesian inference)

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$



- Note: **Marginal likelihood** $p(\mathbf{X}|m)$ is another very important quantity (more on it later)
- Cheaper alternative: Point Estimation of the parameters. E.g.,
  - **Maximum likelihood estimation (MLE):** Find θ that makes the observed data most probable

$$\hat{\theta}_{ML} = \arg\max_{\theta} \log p(\mathbf{X}|\theta)$$

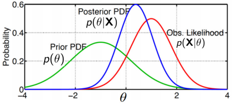
  - **Maximum-a-Posteriori (MAP) estimation:** Find θ that has the largest posterior probability

$$\hat{\theta}_{MAP} = \arg\max_{\theta} \log p(\theta|\mathbf{X})$$

Parameter Estimation/Inference

- Can infer the parameters by computing the posterior distribution (Bayesian inference)

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$



- Note: **Marginal likelihood** $p(\mathbf{X}|m)$ is another very important quantity (more on it later)
- Cheaper alternative: Point Estimation of the parameters. E.g.,
  - **Maximum likelihood estimation (MLE):** Find θ that makes the observed data most probable

$$\hat{\theta}_{ML} = \arg\max_{\theta} \log p(\mathbf{X}|\theta)$$

  - **Maximum-a-Posteriori (MAP) estimation:** Find θ that has the largest posterior probability

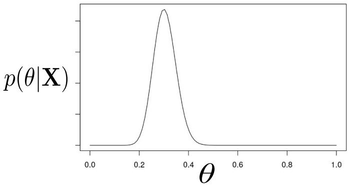
$$\hat{\theta}_{MAP} = \arg\max_{\theta} \log p(\theta|\mathbf{X}) = \arg\max_{\theta}[\log p(\mathbf{X}|\theta) + \log p(\theta)]$$

“Reading” the Posterior Distribution

- Posterior provides us a holistic view about θ given observed data

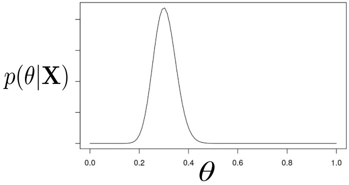
"Reading" the Posterior Distribution

- Posterior provides us a holistic view about θ given observed data
- A simple unimodal posterior distribution for a scalar parameter θ might look something like



"Reading" the Posterior Distribution

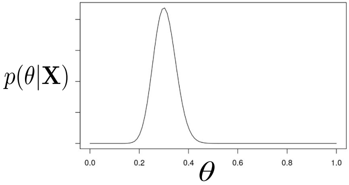
- Posterior provides us a holistic view about θ given observed data
- A simple unimodal posterior distribution for a scalar parameter θ might look something like



- Various types of estimates regarding θ can be obtained from the posterior

“Reading” the Posterior Distribution

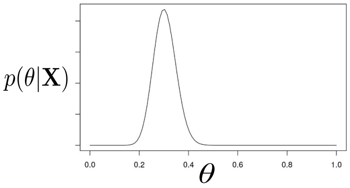
- Posterior provides us a holistic view about θ given observed data
- A simple unimodal posterior distribution for a scalar parameter θ might look something like



- Various types of estimates regarding θ can be obtained from the posterior, e.g.,
  - Mode of the posterior (same as the MAP estimate)

"Reading" the Posterior Distribution

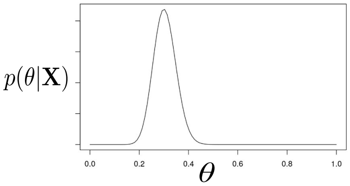
- Posterior provides us a holistic view about θ given observed data
- A simple unimodal posterior distribution for a scalar parameter θ might look something like



- Various types of estimates regarding θ can be obtained from the posterior, e.g.,
  - Mode of the posterior (same as the MAP estimate)
  - Mean and median of the posterior

"Reading" the Posterior Distribution

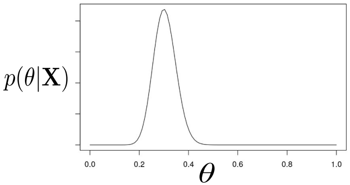
- Posterior provides us a holistic view about θ given observed data
- A simple unimodal posterior distribution for a scalar parameter θ might look something like



- Various types of estimates regarding θ can be obtained from the posterior, e.g.,
  - Mode of the posterior (same as the MAP estimate)
  - Mean and median of the posterior
  - Variance/spread of the posterior (uncertainty in our estimate of the parameters)

"Reading" the Posterior Distribution

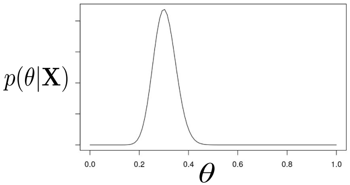
- Posterior provides us a holistic view about θ given observed data
- A simple unimodal posterior distribution for a scalar parameter θ might look something like



- Various types of estimates regarding θ can be obtained from the posterior, e.g.,
  - Mode of the posterior (same as the MAP estimate)
  - Mean and median of the posterior
  - Variance/spread of the posterior (uncertainty in our estimate of the parameters)
  - Any quantile (say $0 < \alpha < 1$ quantile) of the posterior, e.g., θ_* s.t. $p(\theta \leq \theta_*) = \alpha$

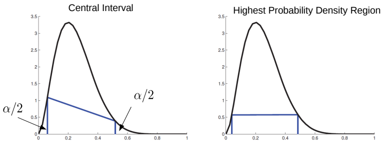
"Reading" the Posterior Distribution

- Posterior provides us a holistic view about θ given observed data
- A simple unimodal posterior distribution for a scalar parameter θ might look something like

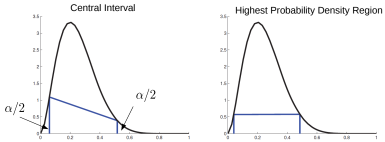


- Various types of estimates regarding θ can be obtained from the posterior, e.g.,
  - Mode of the posterior (same as the MAP estimate)
  - Mean and median of the posterior
  - Variance/spread of the posterior (uncertainty in our estimate of the parameters)
  - Any quantile (say $0 < \alpha < 1$ quantile) of the posterior, e.g., θ_* s.t. $p(\theta \leq \theta_*) = \alpha$
  - Various types of intervals/regions..

“Reading” the Posterior



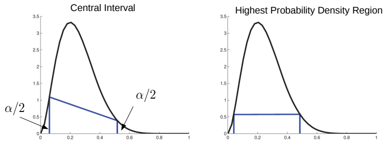
“Reading” the Posterior



- $100(1-\alpha)\%$ Credible interval: Region in which $1-\alpha$ fraction of posterior's mass resides

$$\mathcal{C}_\alpha(\mathbf{X}) = (\ell, u) : p(\ell \le \theta \le u|\mathbf{X}) = 1-\alpha$$

"Reading" the Posterior

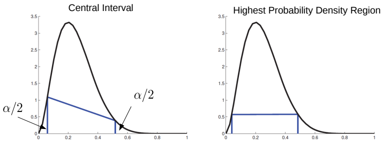


- $100(1-\alpha)\%$ Credible interval: Region in which $1-\alpha$ fraction of posterior's mass resides

$$\mathcal{C}_\alpha(\mathbf{X}) = (\ell, u) : p(\ell \leq \theta \leq u|\mathbf{X}) = 1 - \alpha$$

- Credible Interval is not unique (there can be many $100(1-\alpha)\%$ intervals)

"Reading" the Posterior

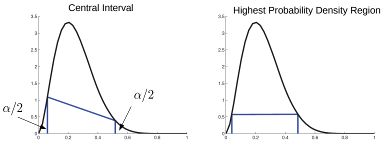


- $100(1-\alpha)\%$ Credible interval: Region in which $1-\alpha$ fraction of posterior's mass resides

$$\mathcal{C}_\alpha(\mathbf{X}) = (\ell, u) : p(\ell \leq \theta \leq u|\mathbf{X}) = 1-\alpha$$

- Credible Interval is not unique (there can be many $100(1-\alpha)\%$ intervals)
- Central Interval is is a symmetrized version of Credible Interval ($\alpha/2$ mass on each tail)

"Reading" the Posterior



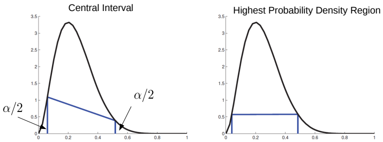
- $100(1-\alpha)\%$ Credible interval: Region in which $1-\alpha$ fraction of posterior's mass resides

$$\mathcal{C}_\alpha(\mathbf{X}) = (\ell, u) : p(\ell \leq \theta \leq u|\mathbf{X}) = 1-\alpha$$

- Credible Interval is not unique (there can be many $100(1-\alpha)\%$ intervals)
- Central Interval is is a symmetrized version of Credible Interval ($\alpha/2$ mass on each tail)
- Another useful interval: The $(1-\alpha)$ Highest Probability Density (HPD) region is defined as

$$\mathcal{C}_\alpha(\mathbf{X}) = \{\theta : p(\theta|\mathbf{X}) \geq p^*\}$$

"Reading" the Posterior



- $100(1-\alpha)\%$ Credible interval: Region in which $1-\alpha$ fraction of posterior's mass resides

$$\mathcal{C}_\alpha(\mathbf{X}) = (\ell, u) : p(\ell \leq \theta \leq u|\mathbf{X}) = 1 - \alpha$$

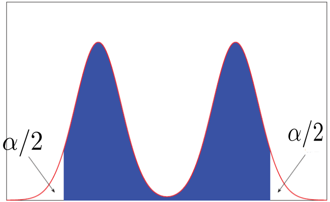
- Credible Interval is not unique (there can be many $100(1-\alpha)\%$ intervals)
- Central Interval is is a symmetrized version of Credible Interval ($\alpha/2$ mass on each tail)
- Another useful interval: The $(1-\alpha)$ Highest Probability Density (HPD) region is defined as

$$\mathcal{C}_\alpha(\mathbf{X}) = \{\theta : p(\theta|\mathbf{X}) \geq p^*\}, \quad \text{s.t.} \quad 1 - \alpha = \int_{\theta: p(\theta|\mathbf{X}) \geq p^*} p(\theta|\mathbf{X}) d\theta$$

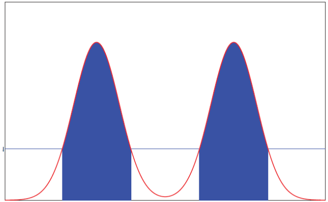
"Reading" the Posterior

- CI, HPD, etc. can also be defined for multi-modal posteriors

Central Interval

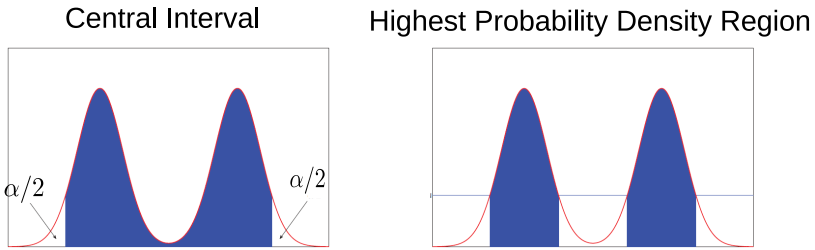


Highest Probability Density Region



"Reading" the Posterior

- CI, HPD, etc. can also be defined for multi-modal posteriors



- Computing quantiles, CI, HPD, etc. may require inverting the CDF of the posterior

Using Posterior for Making Predictions

- Posterior can be used to compute the posterior predictive distribution (PPD) of new observation

Using Posterior for Making Predictions

- Posterior can be used to compute the posterior predictive distribution (PPD) of new observation
- The PPD of a new observation $\boldsymbol{x}_*$ given previous observations

$$p(\boldsymbol{x}_*|\mathbf{X}, m) = \int p(\boldsymbol{x}_*, \theta|\mathbf{X}, m) d\theta$$

Using Posterior for Making Predictions

- Posterior can be used to compute the posterior predictive distribution (PPD) of new observation
- The PPD of a new observation $\boldsymbol{x}_*$ given previous observations

$$p(\boldsymbol{x}_*|\mathbf{X}, m) = \int p(\boldsymbol{x}_*, \theta|\mathbf{X}, m)d\theta \quad = \quad \int p(\boldsymbol{x}_*|\theta, \mathbf{X}, m)p(\theta|\mathbf{X}, m)d\theta$$

Using Posterior for Making Predictions

- Posterior can be used to compute the posterior predictive distribution (PPD) of new observation
- The PPD of a new observation $\boldsymbol{x}_*$ given previous observations

$$p(\boldsymbol{x}_*|\mathbf{X}, m) = \int p(\boldsymbol{x}_*, \theta|\mathbf{X}, m)d\theta = \int p(\boldsymbol{x}_*|\theta, \mathbf{X}, m)p(\theta|\mathbf{X}, m)d\theta$$

$$= \int p(\boldsymbol{x}_*|\theta, m)p(\theta|\mathbf{X}, m)d\theta$$

Using Posterior for Making Predictions

- Posterior can be used to compute the posterior predictive distribution (PPD) of new observation
- The PPD of a new observation $\boldsymbol{x}_*$ given previous observations

$$p(\boldsymbol{x}_*|\mathbf{X}, m) = \int p(\boldsymbol{x}_*, \theta|\mathbf{X}, m)d\theta \quad = \quad \int p(\boldsymbol{x}_*|\theta, \mathbf{X}, m)p(\theta|\mathbf{X}, m)d\theta$$

$$= \int p(\boldsymbol{x}_*|\theta, m)p(\theta|\mathbf{X}, m)d\theta$$

- Note: In the above, we assume that the observations are i.i.d. given θ

Using Posterior for Making Predictions

- Posterior can be used to compute the posterior predictive distribution (PPD) of new observation
- The PPD of a new observation $\boldsymbol{x}_*$ given previous observations

$$p(\boldsymbol{x}_*|\mathbf{X}, m) = \int p(\boldsymbol{x}_*, \theta|\mathbf{X}, m)d\theta \quad = \quad \int p(\boldsymbol{x}_*|\theta, \mathbf{X}, m)p(\theta|\mathbf{X}, m)d\theta$$

$$= \int p(\boldsymbol{x}_*|\theta, m)p(\theta|\mathbf{X}, m)d\theta$$

- Note: In the above, we assume that the observations are i.i.d. given θ
- Computing PPD requires doing a posterior-weighted averaging over all values of θ

Using Posterior for Making Predictions

- Posterior can be used to compute the posterior predictive distribution (PPD) of new observation
- The PPD of a new observation $\boldsymbol{x}_*$ given previous observations

$$p(\boldsymbol{x}_*|\mathbf{X}, m) = \int p(\boldsymbol{x}_*, \theta|\mathbf{X}, m)d\theta \quad = \quad \int p(\boldsymbol{x}_*|\theta, \mathbf{X}, m)p(\theta|\mathbf{X}, m)d\theta$$

$$= \int p(\boldsymbol{x}_*|\theta, m)p(\theta|\mathbf{X}, m)d\theta$$

- Note: In the above, we assume that the observations are i.i.d. given θ
- Computing PPD requires doing a posterior-weighted averaging over all values of θ
- If the integral in PPD is intractable, we can approximate the PPD by plug-in predictive

$$p(\boldsymbol{x}_*|\mathbf{X}, m) \approx p(\boldsymbol{x}_*|\hat{\theta}, m)$$

Using Posterior for Making Predictions

- Posterior can be used to compute the posterior predictive distribution (PPD) of new observation
- The PPD of a new observation $\boldsymbol{x}_*$ given previous observations

$$p(\boldsymbol{x}_*|\mathbf{X}, m) = \int p(\boldsymbol{x}_*, \theta|\mathbf{X}, m)d\theta \quad = \quad \int p(\boldsymbol{x}_*|\theta, \mathbf{X}, m)p(\theta|\mathbf{X}, m)d\theta$$

$$= \int p(\boldsymbol{x}_*|\theta, m)p(\theta|\mathbf{X}, m)d\theta$$

- Note: In the above, we assume that the observations are i.i.d. given θ
- Computing PPD requires doing a posterior-weighted averaging over all values of θ
- If the integral in PPD is intractable, we can approximate the PPD by plug-in predictive

$$p(\boldsymbol{x}_*|\mathbf{X}, m) \approx p(\boldsymbol{x}_*|\hat{\theta}, m)$$

.. where $\hat{\theta}$ is a point estimate of θ (e.g., MLE/MAP)

Using Posterior for Making Predictions

- Posterior can be used to compute the posterior predictive distribution (PPD) of new observation
- The PPD of a new observation $\boldsymbol{x}_*$ given previous observations

$$p(\boldsymbol{x}_*|\mathbf{X}, m) = \int p(\boldsymbol{x}_*, \theta|\mathbf{X}, m)d\theta \quad = \quad \int p(\boldsymbol{x}_*|\theta, \mathbf{X}, m)p(\theta|\mathbf{X}, m)d\theta$$

$$= \int p(\boldsymbol{x}_*|\theta, m)p(\theta|\mathbf{X}, m)d\theta$$

- Note: In the above, we assume that the observations are i.i.d. given θ
- Computing PPD requires doing a posterior-weighted averaging over all values of θ
- If the integral in PPD is intractable, we can approximate the PPD by plug-in predictive

$$p(\boldsymbol{x}_*|\mathbf{X}, m) \approx p(\boldsymbol{x}_*|\hat{\theta}, m)$$

.. where $\hat{\theta}$ is a point estimate of θ (e.g., MLE/MAP)

- The plug-in predictive is the same as PPD with $p(\theta|\mathbf{X}, m)$ approximated by a point mass at $\hat{\theta}$

Marginal Likelihood

- Recall the Bayes rule for computing the posterior

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)}$$

Marginal Likelihood

- Recall the Bayes rule for computing the posterior

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta}$$

Marginal Likelihood

- Recall the Bayes rule for computing the posterior

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$

Marginal Likelihood

- Recall the Bayes rule for computing the posterior

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$

- The denominator in the Bayes rule is the marginal likelihood (a.k.a. "model evidence")

Marginal Likelihood

- Recall the Bayes rule for computing the posterior

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$

- The denominator in the Bayes rule is the marginal likelihood (a.k.a. "model evidence")
- Note that $p(\mathbf{X}|m) = \mathbb{E}_{p(\theta|m)}[p(\mathbf{X}|\theta, m)]$ is the average/expected likelihood under model m

Marginal Likelihood

- Recall the Bayes rule for computing the posterior

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$

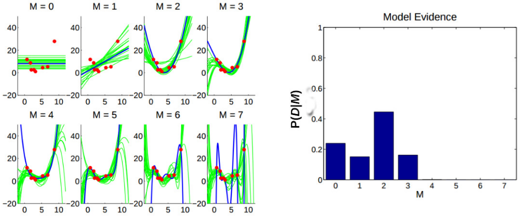
- The denominator in the Bayes rule is the marginal likelihood (a.k.a. "model evidence")
- Note that $p(\mathbf{X}|m) = \mathbb{E}_{p(\theta|m)}[p(\mathbf{X}|\theta, m)]$ is the average/expected likelihood under model m
- For a good model, we would expect this "averaged" quantity to be large (most θ's will be good)

Marginal Likelihood

- Recall the Bayes rule for computing the posterior

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$

- The denominator in the Bayes rule is the marginal likelihood (a.k.a. "model evidence")
- Note that $p(\mathbf{X}|m) = \mathbb{E}_{p(\theta|m)}[p(\mathbf{X}|\theta, m)]$ is the average/expected likelihood under model m
- For a good model, we would expect this "averaged" quantity to be large (most θ's will be good)

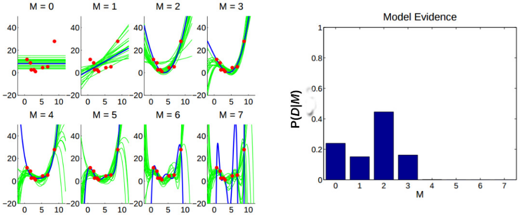


Marginal Likelihood

- Recall the Bayes rule for computing the posterior

$$p(\theta|\mathbf{X}, m) = \frac{p(\mathbf{X}, \theta|m)}{p(\mathbf{X}|m)} = \frac{p(\mathbf{X}|\theta, m)p(\theta|m)}{\int p(\mathbf{X}|\theta, m)p(\theta|m)d\theta} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal likelihood}}$$

- The denominator in the Bayes rule is the marginal likelihood (a.k.a. "model evidence")
- Note that $p(\mathbf{X}|m) = \mathbb{E}_{p(\theta|m)}[p(\mathbf{X}|\theta, m)]$ is the average/expected likelihood under model m
- For a good model, we would expect this "averaged" quantity to be large (most θ's will be good)



- Note that marginal likelihood is also like a "prior predictive distribution"

Model Selection and Model Averaging

- Marginal likelihood is hard-to-compute (due to integral) but a very useful quantity

Model Selection and Model Averaging

- Marginal likelihood is hard-to-compute (due to integral) but a very useful quantity
- It can be used for doing model selection

Model Selection and Model Averaging

- Marginal likelihood is hard-to-compute (due to integral) but a very useful quantity
- It can be used for doing model selection
  - Choose model m that has largest posterior probability

$$\hat{m} = \arg\max_{m} p(m|\mathbf{X})$$

Model Selection and Model Averaging

- Marginal likelihood is hard-to-compute (due to integral) but a very useful quantity
- It can be used for doing model selection
  - Choose model m that has largest posterior probability

$$\hat{m} = \arg\max_m p(m|\mathbf{X}) = \arg\max_m \frac{p(\mathbf{X}|m)p(m)}{p(\mathbf{X})}$$

Model Selection and Model Averaging

- Marginal likelihood is hard-to-compute (due to integral) but a very useful quantity
- It can be used for doing model selection
  - Choose model m that has largest posterior probability

$$\hat{m} = \arg\max_m p(m|\mathbf{X}) = \arg\max_m \frac{p(\mathbf{X}|m)p(m)}{p(\mathbf{X})} = \arg\max_m p(\mathbf{X}|m)p(m)$$

Model Selection and Model Averaging

- Marginal likelihood is hard-to-compute (due to integral) but a very useful quantity
- It can be used for doing model selection
  - Choose model m that has largest posterior probability

$$\hat{m} = \arg\max_m p(m|\mathbf{X}) = \arg\max_m \frac{p(\mathbf{X}|m)p(m)}{p(\mathbf{X})} = \arg\max_m p(\mathbf{X}|m)p(m)$$

  - If all models are equally likely a priori then $\hat{m} = \arg\max_m p(\mathbf{X}|m)$

Model Selection and Model Averaging

- Marginal likelihood is hard-to-compute (due to integral) but a very useful quantity
- It can be used for doing model selection
  - Choose model m that has largest posterior probability

$$\hat{m} = \arg\max_m p(m|\mathbf{X}) = \arg\max_m \frac{p(\mathbf{X}|m)p(m)}{p(\mathbf{X})} = \arg\max_m p(\mathbf{X}|m)p(m)$$

  - If all models are equally likely a priori then $\hat{m} = \arg\max_m p(\mathbf{X}|m)$
  - If m is a hyperparam, then $\arg\max_m p(\mathbf{X}|m)$ is MLE-II based hyperparameter estimation

Model Selection and Model Averaging

- Marginal likelihood is hard-to-compute (due to integral) but a very useful quantity
- It can be used for doing model selection
  - Choose model m that has largest posterior probability

$$\hat{m} = \arg\max_m p(m|\mathbf{X}) = \arg\max_m \frac{p(\mathbf{X}|m)p(m)}{p(\mathbf{X})} = \arg\max_m p(\mathbf{X}|m)p(m)$$

  - If all models are equally likely a priori then $\hat{m} = \arg\max_m p(\mathbf{X}|m)$
  - If m is a hyperparam, then $\arg\max_m p(\mathbf{X}|m)$ is MLE-II based hyperparameter estimation
- Marginal likelihood can be used to compute $p(m|\mathbf{X})$ and then perform Bayesian Model Averaging

$$p(\boldsymbol{x}_*|\mathbf{X}) = \sum_{m=1}^{M} p(\boldsymbol{x}_*|\mathbf{X}, m)p(m|\mathbf{X})$$

Model Selection and Model Averaging

- Marginal likelihood is hard-to-compute (due to integral) but a very useful quantity
- It can be used for doing model selection
  - Choose model m that has largest posterior probability

$$\hat{m} = \arg\max_m p(m|\mathbf{X}) = \arg\max_m \frac{p(\mathbf{X}|m)p(m)}{p(\mathbf{X})} = \arg\max_m p(\mathbf{X}|m)p(m)$$

  - If all models are equally likely a priori then $\hat{m} = \arg\max_m p(\mathbf{X}|m)$
  - If m is a hyperparam, then $\arg\max_m p(\mathbf{X}|m)$ is MLE-II based hyperparameter estimation
- Marginal likelihood can be used to compute $p(m|\mathbf{X})$ and then perform Bayesian Model Averaging

$$p(\boldsymbol{x}_*|\mathbf{X}) = \sum_{m=1}^{M} p(\boldsymbol{x}_*|\mathbf{X}, m)p(m|\mathbf{X})$$

- BMA does a "double" averaging to make prediction since $p(\boldsymbol{x}_*|\mathbf{X}, m) = \int p(\boldsymbol{x}_*|\theta, m)p(\theta|\mathbf{X}, m)d\theta$

A Simple Parameter Estimation Problem

(for a single-parameter model)
(hyperparameter if any will be assumed to be fixed/known)

MLE via a simple example

- Consider a sequence of N coin tosses (call head $= 0$, tail $= 1$)
- The n^{th} outcome $\boldsymbol{x}_n$ is a binary random variable $\in \{0, 1\}$

MLE via a simple example

- Consider a sequence of N coin tosses (call head $= 0$, tail $= 1$)
- The n^{th} outcome $\boldsymbol{x}_n$ is a binary random variable $\in \{0, 1\}$
- Assume θ to be probability of a head (parameter we wish to estimate)

MLE via a simple example

- Consider a sequence of N coin tosses (call head $= 0$, tail $= 1$)
- The n^{th} outcome $\boldsymbol{x}_n$ is a binary random variable $\in \{0, 1\}$
- Assume θ to be probability of a head (parameter we wish to estimate)
- Each likelihood term $p(\boldsymbol{x}_n \mid \theta)$ is Bernoulli: $p(\boldsymbol{x}_n \mid \theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$

MLE via a simple example

- Consider a sequence of N coin tosses (call head $= 0$, tail $= 1$)
- The n^{th} outcome $\boldsymbol{x}_n$ is a binary random variable $\in \{0, 1\}$
- Assume θ to be probability of a head (parameter we wish to estimate)
- Each likelihood term $p(\boldsymbol{x}_n \mid \theta)$ is Bernoulli: $p(\boldsymbol{x}_n \mid \theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$
- Log-likelihood: $\sum_{n=1}^{N} \log p(\boldsymbol{x}_n \mid \theta) = \sum_{n=1}^{N} \boldsymbol{x}_n \log \theta + (1-\boldsymbol{x}_n)\log(1-\theta)$

MLE via a simple example

- Consider a sequence of N coin tosses (call head $= 0$, tail $= 1$)
- The n^{th} outcome $\boldsymbol{x}_n$ is a binary random variable $\in \{0, 1\}$
- Assume θ to be probability of a head (parameter we wish to estimate)
- Each likelihood term $p(\boldsymbol{x}_n \mid \theta)$ is Bernoulli: $p(\boldsymbol{x}_n \mid \theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$
- Log-likelihood: $\sum_{n=1}^{N} \log p(\boldsymbol{x}_n \mid \theta) = \sum_{n=1}^{N} \boldsymbol{x}_n \log \theta + (1 - \boldsymbol{x}_n) \log(1-\theta)$
- Taking derivative of the log-likelihood w.r.t. θ, and setting it to zero gives

$$\hat{\theta}_{MLE} = \frac{\sum_{n=1}^{N} \boldsymbol{x}_n}{N}$$

MLE via a simple example

- Consider a sequence of N coin tosses (call head $= 0$, tail $= 1$)
- The n^{th} outcome $\boldsymbol{x}_n$ is a binary random variable $\in \{0, 1\}$
- Assume θ to be probability of a head (parameter we wish to estimate)
- Each likelihood term $p(\boldsymbol{x}_n \mid \theta)$ is Bernoulli: $p(\boldsymbol{x}_n \mid \theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$
- Log-likelihood: $\sum_{n=1}^{N} \log p(\boldsymbol{x}_n \mid \theta) = \sum_{n=1}^{N} \boldsymbol{x}_n \log \theta + (1 - \boldsymbol{x}_n) \log(1-\theta)$
- Taking derivative of the log-likelihood w.r.t. θ, and setting it to zero gives

$$\hat{\theta}_{MLE} = \frac{\sum_{n=1}^{N} \boldsymbol{x}_n}{N}$$

- $\hat{\theta}_{MLE}$ in this example is simply the fraction of heads!

MLE via a simple example

- Consider a sequence of N coin tosses (call head $= 0$, tail $= 1$)
- The n^{th} outcome $\boldsymbol{x}_n$ is a binary random variable $\in \{0, 1\}$
- Assume θ to be probability of a head (parameter we wish to estimate)
- Each likelihood term $p(\boldsymbol{x}_n \mid \theta)$ is Bernoulli: $p(\boldsymbol{x}_n \mid \theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$
- Log-likelihood: $\sum_{n=1}^{N} \log p(\boldsymbol{x}_n \mid \theta) = \sum_{n=1}^{N} \boldsymbol{x}_n \log \theta + (1-\boldsymbol{x}_n)\log(1-\theta)$
- Taking derivative of the log-likelihood w.r.t. θ, and setting it to zero gives

$$\hat{\theta}_{MLE} = \frac{\sum_{n=1}^{N} \boldsymbol{x}_n}{N}$$

- $\hat{\theta}_{MLE}$ in this example is simply the fraction of heads!
- MLE doesn't have a way to express our prior belief about θ. Can be problematic especially when the number of observations is very small (e.g., suppose very few or zero heads when N is small).

MAP via a simple example

- MAP estimation can incorporate a prior $p(\theta)$ on θ

MAP via a simple example

- MAP estimation can incorporate a prior $p(\theta)$ on θ
- Since $\theta \in (0,1)$, one possibility can be to assume a Beta prior

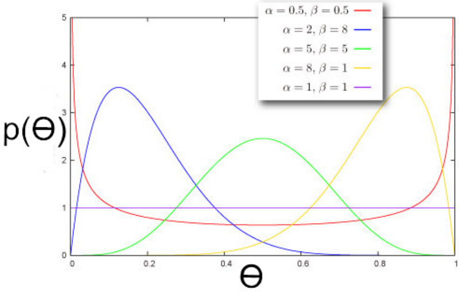
$$p(\theta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$$

MAP via a simple example

- MAP estimation can incorporate a prior $p(\theta)$ on θ
- Since $\theta \in (0,1)$, one possibility can be to assume a Beta prior

$$p(\theta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$$

- α, β are called hyperparameters of the prior (these can have intuitive meaning; we'll see shortly)

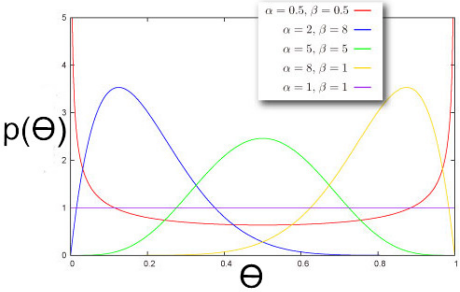


MAP via a simple example

- MAP estimation can incorporate a prior $p(\theta)$ on θ
- Since $\theta \in (0,1)$, one possibility can be to assume a Beta prior

$$p(\theta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$$

- α, β are called hyperparameters of the prior (these can have intuitive meaning; we'll see shortly)



- Note that each likelihood term is still a Bernoulli: $p(x_n|\theta) = \theta^{x_n}(1-\theta)^{1-x_n}$

MAP via a simple example (contd.)

- The log posterior probability $= \sum_{n=1}^{N} \log p(\boldsymbol{x}_n|\theta) + \log p(\theta)$

MAP via a simple example (contd.)

- The log posterior probability $= \sum_{n=1}^{N} \log p(\boldsymbol{x}_n|\theta) + \log p(\theta)$
- Ignoring the constants w.r.t. θ, the log posterior probability:

$$\sum_{n=1}^{N} \{\boldsymbol{x}_n \log \theta + (1 - \boldsymbol{x}_n) \log(1 - \theta)\} + (\alpha - 1) \log \theta + (\beta - 1) \log(1 - \theta)$$

MAP via a simple example (contd.)

- The log posterior probability $= \sum_{n=1}^{N} \log p(\boldsymbol{x}_n|\theta) + \log p(\theta)$
- Ignoring the constants w.r.t. θ, the log posterior probability:

$$\sum_{n=1}^{N}\{\boldsymbol{x}_n \log\theta + (1-\boldsymbol{x}_n)\log(1-\theta)\} + (\alpha-1)\log\theta + (\beta-1)\log(1-\theta)$$

- Taking derivative w.r.t. θ and setting to zero gives

$$\hat{\theta}_{MAP} = \frac{\sum_{n=1}^{N}\boldsymbol{x}_n + \alpha - 1}{N+\alpha+\beta-2}$$

MAP via a simple example (contd.)

- The log posterior probability $= \sum_{n=1}^{N} \log p(\boldsymbol{x}_n|\theta) + \log p(\theta)$
- Ignoring the constants w.r.t. θ, the log posterior probability:

$$\sum_{n=1}^{N}\{\boldsymbol{x}_n \log\theta + (1-\boldsymbol{x}_n)\log(1-\theta)\} + (\alpha-1)\log\theta + (\beta-1)\log(1-\theta)$$

- Taking derivative w.r.t. θ and setting to zero gives

$$\hat{\theta}_{MAP} = \frac{\sum_{n=1}^{N}\boldsymbol{x}_n + \alpha - 1}{N+\alpha+\beta-2}$$

- Note: For $\alpha = 1, \beta = 1$, i.e., $p(\theta) = \text{Beta}(1,1)$ (equivalent to a uniform prior), $\hat{\theta}_{MAP} = \hat{\theta}_{MLE}$

MAP via a simple example (contd.)

- The log posterior probability $= \sum_{n=1}^{N} \log p(\boldsymbol{x}_n|\theta) + \log p(\theta)$
- Ignoring the constants w.r.t. θ, the log posterior probability:

$$\sum_{n=1}^{N}\{\boldsymbol{x}_n \log\theta + (1-\boldsymbol{x}_n)\log(1-\theta)\} + (\alpha-1)\log\theta + (\beta-1)\log(1-\theta)$$

- Taking derivative w.r.t. θ and setting to zero gives

$$\hat{\theta}_{MAP} = \frac{\sum_{n=1}^{N}\boldsymbol{x}_n + \alpha - 1}{N+\alpha+\beta-2}$$

- Note: For $\alpha = 1, \beta = 1$, i.e., $p(\theta) = \text{Beta}(1,1)$ (equivalent to a uniform prior), $\hat{\theta}_{MAP} = \hat{\theta}_{MLE}$
- What hyperparameters represent intuitively? Hyperparameters of the prior (in this case α, β) can often be thought of as "pseudo-observations".

MAP via a simple example (contd.)

- The log posterior probability $= \sum_{n=1}^{N} \log p(\boldsymbol{x}_n|\theta) + \log p(\theta)$
- Ignoring the constants w.r.t. θ, the log posterior probability:

$$\sum_{n=1}^{N}\{\boldsymbol{x}_n \log\theta + (1-\boldsymbol{x}_n)\log(1-\theta)\} + (\alpha-1)\log\theta + (\beta-1)\log(1-\theta)$$

- Taking derivative w.r.t. θ and setting to zero gives

$$\hat{\theta}_{MAP} = \frac{\sum_{n=1}^{N}\boldsymbol{x}_n + \alpha - 1}{N+\alpha+\beta-2}$$

- Note: For $\alpha = 1, \beta = 1$, i.e., $p(\theta) = \text{Beta}(1,1)$ (equivalent to a uniform prior), $\hat{\theta}_{MAP} = \hat{\theta}_{MLE}$
- What hyperparameters represent intuitively? Hyperparameters of the prior (in this case α, β) can often be thought of as "pseudo-observations".
  - $\alpha-1$, $\beta-1$ are the expected numbers of heads and tails, respectively, before seeing any data

Full Bayesian Inference via a simple example

- Recall that each likelihood term was Bernoulli: $p(\boldsymbol{x}_n|\theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$
- Let's again choose the prior $p(\theta)$ as Beta: $p(\theta) = \text{Beta}(\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$

Full Bayesian Inference via a simple example

- Recall that each likelihood term was Bernoulli: $p(\boldsymbol{x}_n|\theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$
- Let's again choose the prior $p(\theta)$ as Beta: $p(\theta) = \text{Beta}(\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$
- The posterior distribution will be proportional to the product of likelihood and prior

$$
\begin{aligned}
p(\theta|\mathbf{X}) &\propto \prod_{n=1}^{N} p(\boldsymbol{x}_n|\theta)p(\theta) \\
&\propto \theta^{\alpha+\sum_{n=1}^{N}\boldsymbol{x}_n-1}(1-\theta)^{\beta+N-\sum_{n=1}^{N}\boldsymbol{x}_n-1}
\end{aligned}
$$

Full Bayesian Inference via a simple example

- Recall that each likelihood term was Bernoulli: $p(\boldsymbol{x}_n|\theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$
- Let's again choose the prior $p(\theta)$ as Beta: $p(\theta) = \text{Beta}(\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$
- The posterior distribution will be proportional to the product of likelihood and prior

$$
\begin{aligned}
p(\theta|\mathbf{X}) &\propto \prod_{n=1}^{N} p(\boldsymbol{x}_n|\theta)p(\theta) \\
&\propto \theta^{\alpha+\sum_{n=1}^{N}\boldsymbol{x}_n-1}(1-\theta)^{\beta+N-\sum_{n=1}^{N}\boldsymbol{x}_n-1}
\end{aligned}
$$

- From simple inspection, note that the posterior $p(\theta|\mathbf{X}) = \text{Beta}(\alpha+\sum_{n=1}^{N}\boldsymbol{x}_n, \beta+N-\sum_{n=1}^{N}\boldsymbol{x}_n)$

Full Bayesian Inference via a simple example

- Recall that each likelihood term was Bernoulli: $p(\boldsymbol{x}_n|\theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$
- Let's again choose the prior $p(\theta)$ as Beta: $p(\theta) = \text{Beta}(\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$
- The posterior distribution will be proportional to the product of likelihood and prior

$$
\begin{aligned}
p(\theta|\mathbf{X}) &\propto \prod_{n=1}^{N} p(\boldsymbol{x}_n|\theta)p(\theta) \\
&\propto \theta^{\alpha+\sum_{n=1}^{N}\boldsymbol{x}_n-1}(1-\theta)^{\beta+N-\sum_{n=1}^{N}\boldsymbol{x}_n-1}
\end{aligned}
$$

- From simple inspection, note that the posterior $p(\theta|\mathbf{X}) = \text{Beta}(\alpha + \sum_{n=1}^{N}\boldsymbol{x}_n, \beta + N - \sum_{n=1}^{N}\boldsymbol{x}_n)$
- Here, finding the posterior boiled down to simply "multipy, add stuff, and identify the distribution"

Full Bayesian Inference via a simple example

- Recall that each likelihood term was Bernoulli: $p(\boldsymbol{x}_n|\theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$
- Let's again choose the prior $p(\theta)$ as Beta: $p(\theta) = \text{Beta}(\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$
- The posterior distribution will be proportional to the product of likelihood and prior

$$
\begin{aligned}
p(\theta|\mathbf{X}) &\propto \prod_{n=1}^{N} p(\boldsymbol{x}_n|\theta)p(\theta) \\
&\propto \theta^{\alpha+\sum_{n=1}^{N}\boldsymbol{x}_n-1}(1-\theta)^{\beta+N-\sum_{n=1}^{N}\boldsymbol{x}_n-1}
\end{aligned}
$$

- From simple inspection, note that the posterior $p(\theta|\mathbf{X}) = \text{Beta}(\alpha + \sum_{n=1}^{N}\boldsymbol{x}_n, \beta + N - \sum_{n=1}^{N}\boldsymbol{x}_n)$
- Here, finding the posterior boiled down to simply "multipy, add stuff, and identify the distribution"
- Note: Can verify (exercise) that the normalization constant $= \frac{\Gamma(\alpha+\sum_{n=1}^{N}\boldsymbol{x}_n)\Gamma(\beta+N-\sum_{n=1}^{N}\boldsymbol{x}_n)}{\Gamma(\alpha+\beta+N)}$
    - To verify, make use of the fact that $\int p(\theta|\mathbf{X})d\theta = 1$

Full Bayesian Inference via a simple example

- Recall that each likelihood term was Bernoulli: $p(\boldsymbol{x}_n|\theta) = \theta^{\boldsymbol{x}_n}(1-\theta)^{1-\boldsymbol{x}_n}$
- Let's again choose the prior $p(\theta)$ as Beta: $p(\theta) = \text{Beta}(\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$
- The posterior distribution will be proportional to the product of likelihood and prior

$$\begin{aligned} p(\theta|\mathbf{X}) &\propto \prod_{n=1}^{N} p(\boldsymbol{x}_n|\theta)p(\theta) \\ &\propto \theta^{\alpha+\sum_{n=1}^{N}\boldsymbol{x}_n-1}(1-\theta)^{\beta+N-\sum_{n=1}^{N}\boldsymbol{x}_n-1} \end{aligned}$$

- From simple inspection, note that the posterior $p(\theta|\mathbf{X}) = \text{Beta}(\alpha+\sum_{n=1}^{N}\boldsymbol{x}_n, \beta+N-\sum_{n=1}^{N}\boldsymbol{x}_n)$
- Here, finding the posterior boiled down to simply "multipy, add stuff, and identify the distribution"
- Note: Can verify (exercise) that the normalization constant $= \frac{\Gamma(\alpha+\sum_{n=1}^{N}\boldsymbol{x}_n)\Gamma(\beta+N-\sum_{n=1}^{N}\boldsymbol{x}_n)}{\Gamma(\alpha+\beta+N)}$
  - To verify, make use of the fact that $\int p(\theta|\mathbf{X})d\theta = 1$
- Here, the posterior has the same form as the prior (both Beta): property of **conjugate priors**.

Conjugate Priors

- Many pairs of distributions are conjugate to each other. E.g.,
  - Bernoulli (likelihood) + Beta (prior) $\Rightarrow$ Beta posterior
  - Binomial (likelihood) + Beta (prior) $\Rightarrow$ Beta posterior
  - Multinomial (likelihood) + Dirichlet (prior) $\Rightarrow$ Dirichlet posterior
  - Poisson (likelihood) + Gamma (prior) $\Rightarrow$ Gamma posterior
  - Gaussian (likelihood) + Gaussian (prior) $\Rightarrow$ Gaussian posterior
  - and many other such pairs ..

Conjugate Priors

- Many pairs of distributions are conjugate to each other. E.g.,
  - Bernoulli (likelihood) + Beta (prior) $\Rightarrow$ Beta posterior
  - Binomial (likelihood) + Beta (prior) $\Rightarrow$ Beta posterior
  - Multinomial (likelihood) + Dirichlet (prior) $\Rightarrow$ Dirichlet posterior
  - Poisson (likelihood) + Gamma (prior) $\Rightarrow$ Gamma posterior
  - Gaussian (likelihood) + Gaussian (prior) $\Rightarrow$ Gaussian posterior
  - and many other such pairs ..
- Easy to identify if two distributions are conjugate to each other: their functional forms are similar
  - E.g., recall the forms of Bernoulli and Beta

$$\text{Bernoulli} \propto \theta^{x}(1-\theta)^{1-x}, \quad \text{Beta} \propto \theta^{\alpha-1}(1-\theta)^{\beta-1}$$

Conjugate Priors

- Many pairs of distributions are conjugate to each other. E.g.,
  - Bernoulli (likelihood) + Beta (prior) $\Rightarrow$ Beta posterior
  - Binomial (likelihood) + Beta (prior) $\Rightarrow$ Beta posterior
  - Multinomial (likelihood) + Dirichlet (prior) $\Rightarrow$ Dirichlet posterior
  - Poisson (likelihood) + Gamma (prior) $\Rightarrow$ Gamma posterior
  - Gaussian (likelihood) + Gaussian (prior) $\Rightarrow$ Gaussian posterior
  - and many other such pairs ..
- Easy to identify if two distributions are conjugate to each other: their functional forms are similar
  - E.g., recall the forms of Bernoulli and Beta

$$\text{Bernoulli} \propto \theta^x(1-\theta)^{1-x}, \quad \text{Beta} \propto \theta^{\alpha-1}(1-\theta)^{\beta-1}$$

- More on conjugate priors when we look at exponental family distributions

Making Predictions

- Let's say we want to compute the probability that the next outcome $\boldsymbol{x}_{N+1} \in \{0, 1\}$ will be a head

Making Predictions

- Let's say we want to compute the probability that the next outcome $\boldsymbol{x}_{N+1} \in \{0,1\}$ will be a head
- The plug-in predictive distribution using a point estimate $\hat{\theta}$ (e.g., using MLE/MAP)

$$p(\boldsymbol{x}_{N+1} = 1|\mathbf{X}) \approx p(\boldsymbol{x}_{N+1} = 1|\hat{\theta}) = \hat{\theta} \qquad \underline{\text{or equivalently}} \qquad p(\boldsymbol{x}_{N+1}|\mathbf{X}) \approx \text{Bernoulli}(\boldsymbol{x}_{N+1} \mid \hat{\theta})$$

Making Predictions

- Let's say we want to compute the probability that the next outcome $\boldsymbol{x}_{N+1} \in \{0, 1\}$ will be a head
- The plug-in predictive distribution using a point estimate $\hat{\theta}$ (e.g., using MLE/MAP)

$$p(\boldsymbol{x}_{N+1} = 1|\mathbf{X}) \approx p(\boldsymbol{x}_{N+1} = 1|\hat{\theta}) = \hat{\theta} \quad \underline{\text{or equivalently}} \quad p(\boldsymbol{x}_{N+1}|\mathbf{X}) \approx \text{Bernoulli}(\boldsymbol{x}_{N+1} \mid \hat{\theta})$$

- The posterior predictive distribution (averaging over all θ weighted by their posterior probabilities):

$$p(\boldsymbol{x}_{N+1} = 1|\mathbf{X}) = \int_0^1 P(\boldsymbol{x}_{N+1} = 1|\theta)p(\theta|\mathbf{X})d\theta$$

Making Predictions

- Let's say we want to compute the probability that the next outcome $\boldsymbol{x}_{N+1} \in \{0, 1\}$ will be a head
- The plug-in predictive distribution using a point estimate $\hat{\theta}$ (e.g., using MLE/MAP)

$$p(\boldsymbol{x}_{N+1} = 1|\mathbf{X}) \approx p(\boldsymbol{x}_{N+1} = 1|\hat{\theta}) = \hat{\theta} \qquad \underline{\text{or equivalently}} \qquad p(\boldsymbol{x}_{N+1}|\mathbf{X}) \approx \text{Bernoulli}(\boldsymbol{x}_{N+1} \mid \hat{\theta})$$

- The posterior predictive distribution (averaging over all θ weighted by their posterior probabilities):

$$\begin{aligned} p(\boldsymbol{x}_{N+1} = 1|\mathbf{X}) &= \int_0^1 P(\boldsymbol{x}_{N+1} = 1|\theta)p(\theta|\mathbf{X})d\theta \\ &= \int_0^1 \theta \times \text{Beta}(\theta|\alpha + N_1, \beta + N_0)d\theta \end{aligned}$$

Making Predictions

- Let's say we want to compute the probability that the next outcome $\boldsymbol{x}_{N+1} \in \{0,1\}$ will be a head
- The plug-in predictive distribution using a point estimate $\hat{\theta}$ (e.g., using MLE/MAP)

$$p(x_{N+1} = 1|\mathbf{X}) \approx p(x_{N+1} = 1|\hat{\theta}) = \hat{\theta} \qquad \underline{\text{or equivalently}} \qquad p(x_{N+1}|\mathbf{X}) \approx \text{Bernoulli}(x_{N+1} \mid \hat{\theta})$$

- The posterior predictive distribution (averaging over all θ weighted by their posterior probabilities):

$$\begin{aligned} p(x_{N+1} = 1|\mathbf{X}) &= \int_0^1 P(x_{N+1} = 1|\theta)p(\theta|\mathbf{X})d\theta \\ &= \int_0^1 \theta \times \text{Beta}(\theta|\alpha + N_1, \beta + N_0)d\theta \\ &= \mathbb{E}[\theta|\mathbf{X}] \end{aligned}$$

Making Predictions

- Let's say we want to compute the probability that the next outcome $\boldsymbol{x}_{N+1} \in \{0, 1\}$ will be a head
- The plug-in predictive distribution using a point estimate $\hat{\theta}$ (e.g., using MLE/MAP)

$$p(\boldsymbol{x}_{N+1} = 1|\mathbf{X}) \approx p(\boldsymbol{x}_{N+1} = 1|\hat{\theta}) = \hat{\theta} \quad \underline{\text{or equivalently}} \quad p(\boldsymbol{x}_{N+1}|\mathbf{X}) \approx \text{Bernoulli}(\boldsymbol{x}_{N+1} \mid \hat{\theta})$$

- The posterior predictive distribution (averaging over all θ weighted by their posterior probabilities):

$$\begin{aligned} p(\boldsymbol{x}_{N+1} = 1|\mathbf{X}) &= \int_0^1 P(\boldsymbol{x}_{N+1} = 1|\theta) p(\theta|\mathbf{X}) d\theta \\ &= \int_0^1 \theta \times \text{Beta}(\theta|\alpha + N_1, \beta + N_0) d\theta \\ &= \mathbb{E}[\theta|\mathbf{X}] \\ &= \frac{\alpha + N_1}{\alpha + \beta + N} \end{aligned}$$

Making Predictions

- Let's say we want to compute the probability that the next outcome $\boldsymbol{x}_{N+1} \in \{0, 1\}$ will be a head
- The plug-in predictive distribution using a point estimate $\hat{\theta}$ (e.g., using MLE/MAP)

$$p(\boldsymbol{x}_{N+1} = 1|\mathbf{X}) \approx p(\boldsymbol{x}_{N+1} = 1|\hat{\theta}) = \hat{\theta} \qquad \underline{\text{or equivalently}} \qquad p(\boldsymbol{x}_{N+1}|\mathbf{X}) \approx \text{Bernoulli}(\boldsymbol{x}_{N+1} \mid \hat{\theta})$$

- The posterior predictive distribution (averaging over all θ weighted by their posterior probabilities):

$$\begin{aligned} p(\boldsymbol{x}_{N+1} = 1|\mathbf{X}) &= \int_0^1 P(\boldsymbol{x}_{N+1} = 1|\theta) p(\theta|\mathbf{X}) d\theta \\ &= \int_0^1 \theta \times \text{Beta}(\theta|\alpha + N_1, \beta + N_0) d\theta \\ &= \mathbb{E}[\theta|\mathbf{X}] \\ &= \frac{\alpha + N_1}{\alpha + \beta + N} \end{aligned}$$

- Therefore the posterior predictive distribution: $p(\boldsymbol{x}_{N+1}|\mathbf{X}) = \text{Bernoulli}(\boldsymbol{x}_{N+1} \mid \mathbb{E}[\theta|\mathbf{X}])$

Another Example: Estimating Gaussian Mean

- Consider N i.i.d. observations $\mathbf{X} = \{x_1, \ldots, x_N\}$ drawn from a one-dim Gaussian $\mathcal{N}(x|\mu, \sigma^2)$

$$
\begin{aligned}
p(x_n|\mu, \sigma^2) &= \mathcal{N}(x|\mu, \sigma^2) \propto \exp\left[-\frac{(x_n - \mu)^2}{2\sigma^2}\right] \\
p(\mathbf{X}|\mu, \sigma^2) &= \prod_{n=1}^{N} p(x_n|\mu, \sigma^2)
\end{aligned}
$$

Another Example: Estimating Gaussian Mean

- Consider N i.i.d. observations $\mathbf{X} = \{x_1, \ldots, x_N\}$ drawn from a one-dim Gaussian $\mathcal{N}(x|\mu, \sigma^2)$

$$
\begin{aligned}
p(x_n|\mu, \sigma^2) &= \mathcal{N}(x|\mu, \sigma^2) \propto \exp\left[-\frac{(x_n - \mu)^2}{2\sigma^2}\right] \\
p(\mathbf{X}|\mu, \sigma^2) &= \prod_{n=1}^{N} p(x_n|\mu, \sigma^2)
\end{aligned}
$$

- Assume the mean $\mu \in \mathbb{R}$ of the Gaussian is unknown and assume variance σ^2 to be known/fixed

Another Example: Estimating Gaussian Mean

- Consider N i.i.d. observations $\mathbf{X} = \{x_1, \ldots, x_N\}$ drawn from a one-dim Gaussian $\mathcal{N}(x|\mu, \sigma^2)$

$$
\begin{aligned}
p(x_n|\mu, \sigma^2) &= \mathcal{N}(x|\mu, \sigma^2) \propto \exp\left[-\frac{(x_n - \mu)^2}{2\sigma^2}\right] \\
p(\mathbf{X}|\mu, \sigma^2) &= \prod_{n=1}^{N} p(x_n|\mu, \sigma^2)
\end{aligned}
$$

- Assume the mean $\mu \in \mathbb{R}$ of the Gaussian is unknown and assume variance σ^2 to be known/fixed
- We wish to estimate the unknown μ given the data $\mathbf{X}$

Another Example: Estimating Gaussian Mean

- Consider N i.i.d. observations $\mathbf{X} = \{x_1, \ldots, x_N\}$ drawn from a one-dim Gaussian $\mathcal{N}(x|\mu, \sigma^2)$

$$
\begin{aligned}
p(x_n|\mu, \sigma^2) &= \mathcal{N}(x|\mu, \sigma^2) \propto \exp\left[-\frac{(x_n - \mu)^2}{2\sigma^2}\right] \\
p(\mathbf{X}|\mu, \sigma^2) &= \prod_{n=1}^{N} p(x_n|\mu, \sigma^2)
\end{aligned}
$$

- Assume the mean $\mu \in \mathbb{R}$ of the Gaussian is unknown and assume variance σ^2 to be known/fixed
- We wish to estimate the unknown μ given the data $\mathbf{X}$
- Let's do fully Bayesian inference for μ (not MLE/MAP)

Another Example: Estimating Gaussian Mean

- Consider N i.i.d. observations $\mathbf{X} = \{x_1, \ldots, x_N\}$ drawn from a one-dim Gaussian $\mathcal{N}(x|\mu, \sigma^2)$

$$
\begin{aligned}
p(x_n|\mu, \sigma^2) &= \mathcal{N}(x|\mu, \sigma^2) \propto \exp\left[-\frac{(x_n - \mu)^2}{2\sigma^2}\right] \\
p(\mathbf{X}|\mu, \sigma^2) &= \prod_{n=1}^{N} p(x_n|\mu, \sigma^2)
\end{aligned}
$$

- Assume the mean $\mu \in \mathbb{R}$ of the Gaussian is unknown and assume variance σ^2 to be known/fixed
- We wish to estimate the unknown μ given the data $\mathbf{X}$
- Let's do fully Bayesian inference for μ (not MLE/MAP)
- We first need a prior distribution for the unknown param. μ

Another Example: Estimating Gaussian Mean

- Consider N i.i.d. observations $\mathbf{X} = \{x_1, \ldots, x_N\}$ drawn from a one-dim Gaussian $\mathcal{N}(x|\mu, \sigma^2)$

$$
\begin{aligned}
p(x_n|\mu, \sigma^2) &= \mathcal{N}(x|\mu, \sigma^2) \propto \exp\left[-\frac{(x_n - \mu)^2}{2\sigma^2}\right] \\
p(\mathbf{X}|\mu, \sigma^2) &= \prod_{n=1}^{N} p(x_n|\mu, \sigma^2)
\end{aligned}
$$

- Assume the mean $\mu \in \mathbb{R}$ of the Gaussian is unknown and assume variance σ^2 to be known/fixed
- We wish to estimate the unknown μ given the data $\mathbf{X}$
- Let's do fully Bayesian inference for μ (not MLE/MAP)
- We first need a prior distribution for the unknown param. μ
- Let's choose a Gaussian prior on μ, i.e., $p(\mu) = \mathcal{N}(\mu|\mu_0, \sigma_0^2)$ with μ_0, σ_0^2 as fixed

Another Example: Estimating Gaussian Mean

- Consider N i.i.d. observations $\mathbf{X} = \{x_1, \ldots, x_N\}$ drawn from a one-dim Gaussian $\mathcal{N}(x|\mu, \sigma^2)$

$$p(x_n|\mu, \sigma^2) = \mathcal{N}(x|\mu, \sigma^2) \propto \exp\left[-\frac{(x_n - \mu)^2}{2\sigma^2}\right]$$

$$p(\mathbf{X}|\mu, \sigma^2) = \prod_{n=1}^{N} p(x_n|\mu, \sigma^2)$$

- Assume the mean $\mu \in \mathbb{R}$ of the Gaussian is unknown and assume variance σ^2 to be known/fixed
- We wish to estimate the unknown μ given the data $\mathbf{X}$
- Let's do fully Bayesian inference for μ (not MLE/MAP)
- We first need a prior distribution for the unknown param. μ
- Let's choose a Gaussian prior on μ, i.e., $p(\mu) = \mathcal{N}(\mu|\mu_0, \sigma_0^2)$ with μ_0, σ_0^2 as fixed
- Therefore this is also a single-parameter model (only μ is the unknown)

Another Example: Estimating Gaussian Mean

- The posterior distribution for the unknown mean parameter μ

$$p(\mu|\mathbf{X}) = \frac{p(\mathbf{X}|\mu)p(\mu)}{p(\mathbf{X})} \quad \propto \quad \prod_{n=1}^{N} \exp\left[-\frac{(x_n-\mu)^2}{2\sigma^2}\right] \times \exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right]$$

Another Example: Estimating Gaussian Mean

- The posterior distribution for the unknown mean parameter μ

$$p(\mu|\mathbf{X}) = \frac{p(\mathbf{X}|\mu)p(\mu)}{p(\mathbf{X})} \quad \propto \quad \prod_{n=1}^{N} \exp\left[-\frac{(x_n-\mu)^2}{2\sigma^2}\right] \times \exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right]$$

- (Verify) The above posterior turns out to be another Gaussian $p(\mu|\mathbf{X}) = \mathcal{N}(\mu|\mu_N, \sigma_N^2)$ where

$$\frac{1}{\sigma_N^2} = \frac{N}{\sigma^2} + \frac{1}{\sigma_0^2}$$

$$\mu_N = \frac{\sigma^2}{N\sigma_0^2 + \sigma^2}\mu_0 + \frac{N\sigma_0^2}{N\sigma_0^2 + \sigma^2}\bar{x} \qquad \text{(where } \bar{x} = \frac{\sum_{n=1}^{N} x_n}{N}\text{)}$$

Another Example: Estimating Gaussian Mean

- The posterior distribution for the unknown mean parameter μ

$$p(\mu|\mathbf{X}) = \frac{p(\mathbf{X}|\mu)p(\mu)}{p(\mathbf{X})} \propto \prod_{n=1}^{N} \exp\left[-\frac{(x_n-\mu)^2}{2\sigma^2}\right] \times \exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right]$$

- (Verify) The above posterior turns out to be another Gaussian $p(\mu|\mathbf{X}) = \mathcal{N}(\mu|\mu_N, \sigma_N^2)$ where

$$\frac{1}{\sigma_N^2} = \frac{N}{\sigma^2} + \frac{1}{\sigma_0^2}$$

$$\mu_N = \frac{\sigma^2}{N\sigma_0^2 + \sigma^2}\mu_0 + \frac{N\sigma_0^2}{N\sigma_0^2 + \sigma^2}\bar{x} \qquad \text{(where } \bar{x} = \frac{\sum_{n=1}^{N} x_n}{N}\text{)}$$

- Making prediction: The posterior predictive distribution for a new observation x_* will be

$$p(x_*|\mathbf{X}) = \int p(x_*|\mu)p(\mu|\mathbf{X})d\mu$$

Another Example: Estimating Gaussian Mean

- The posterior distribution for the unknown mean parameter μ

$$p(\mu|\mathbf{X}) = \frac{p(\mathbf{X}|\mu)p(\mu)}{p(\mathbf{X})} \propto \prod_{n=1}^{N} \exp\left[-\frac{(x_n-\mu)^2}{2\sigma^2}\right] \times \exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right]$$

- (Verify) The above posterior turns out to be another Gaussian $p(\mu|\mathbf{X}) = \mathcal{N}(\mu|\mu_N, \sigma_N^2)$ where

$$\frac{1}{\sigma_N^2} = \frac{N}{\sigma^2} + \frac{1}{\sigma_0^2}$$

$$\mu_N = \frac{\sigma^2}{N\sigma_0^2+\sigma^2}\mu_0 + \frac{N\sigma_0^2}{N\sigma_0^2+\sigma^2}\bar{x} \qquad \left(\text{where } \bar{x} = \frac{\sum_{n=1}^{N} x_n}{N}\right)$$

- Making prediction: The posterior predictive distribution for a new observation x_* will be

$$p(x_*|\mathbf{X}) = \int p(x_*|\mu)p(\mu|\mathbf{X})d\mu = \int \mathcal{N}(x_*|\mu,\sigma^2)\mathcal{N}(\mu|\mu_N,\sigma_N^2)d\mu$$

Another Example: Estimating Gaussian Mean

- The posterior distribution for the unknown mean parameter μ

$$p(\mu|\mathbf{X}) = \frac{p(\mathbf{X}|\mu)p(\mu)}{p(\mathbf{X})} \quad \propto \quad \prod_{n=1}^{N} \exp\left[-\frac{(x_n-\mu)^2}{2\sigma^2}\right] \times \exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right]$$

- (Verify) The above posterior turns out to be another Gaussian $p(\mu|\mathbf{X}) = \mathcal{N}(\mu|\mu_N, \sigma_N^2)$ where

$$\frac{1}{\sigma_N^2} = \frac{N}{\sigma^2} + \frac{1}{\sigma_0^2}$$

$$\mu_N = \frac{\sigma^2}{N\sigma_0^2+\sigma^2}\mu_0 + \frac{N\sigma_0^2}{N\sigma_0^2+\sigma^2}\bar{x} \qquad \left(\text{where } \bar{x} = \frac{\sum_{n=1}^{N} x_n}{N}\right)$$

- Making prediction: The posterior predictive distribution for a new observation x_* will be

$$p(x_*|\mathbf{X}) = \int p(x_*|\mu)p(\mu|\mathbf{X})d\mu = \int \mathcal{N}(x_*|\mu,\sigma^2)\mathcal{N}(\mu|\mu_N,\sigma_N^2)d\mu = \mathcal{N}(x_*|\mu_N,\sigma_N^2+\sigma^2)$$

Another Example: Estimating Gaussian Mean

- The posterior distribution for the unknown mean parameter μ

$$p(\mu|\mathbf{X}) = \frac{p(\mathbf{X}|\mu)p(\mu)}{p(\mathbf{X})} \propto \prod_{n=1}^{N} \exp\left[-\frac{(x_n-\mu)^2}{2\sigma^2}\right] \times \exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right]$$

- (Verify) The above posterior turns out to be another Gaussian $p(\mu|\mathbf{X}) = \mathcal{N}(\mu|\mu_N, \sigma_N^2)$ where

$$\frac{1}{\sigma_N^2} = \frac{N}{\sigma^2} + \frac{1}{\sigma_0^2}$$

$$\mu_N = \frac{\sigma^2}{N\sigma_0^2+\sigma^2}\mu_0 + \frac{N\sigma_0^2}{N\sigma_0^2+\sigma^2}\bar{x} \qquad \left(\text{where } \bar{x} = \frac{\sum_{n=1}^{N} x_n}{N}\right)$$

- Making prediction: The posterior predictive distribution for a new observation x_* will be

$$p(x_*|\mathbf{X}) = \int p(x_*|\mu)p(\mu|\mathbf{X})d\mu = \int \mathcal{N}(x_*|\mu,\sigma^2)\mathcal{N}(\mu|\mu_N,\sigma_N^2)d\mu = \mathcal{N}(x_*|\mu_N,\sigma_N^2+\sigma^2)$$

- Note that, in contrast, the plug-in predictive posterior, given a point estimate $\hat{\mu}$ would be

$$p(x_*|\mathbf{X}) = \int p(x_*|\mu)p(\mu|\mathbf{X})d\mu$$

Another Example: Estimating Gaussian Mean

- The posterior distribution for the unknown mean parameter μ

$$p(\mu|\mathbf{X}) = \frac{p(\mathbf{X}|\mu)p(\mu)}{p(\mathbf{X})} \quad \propto \quad \prod_{n=1}^{N} \exp\left[-\frac{(x_n-\mu)^2}{2\sigma^2}\right] \times \exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right]$$

- (Verify) The above posterior turns out to be another Gaussian $p(\mu|\mathbf{X}) = \mathcal{N}(\mu|\mu_N, \sigma_N^2)$ where

$$\frac{1}{\sigma_N^2} = \frac{N}{\sigma^2} + \frac{1}{\sigma_0^2}$$

$$\mu_N = \frac{\sigma^2}{N\sigma_0^2+\sigma^2}\mu_0 + \frac{N\sigma_0^2}{N\sigma_0^2+\sigma^2}\bar{x} \qquad \left(\text{where } \bar{x} = \frac{\sum_{n=1}^{N} x_n}{N}\right)$$

- Making prediction: The posterior predictive distribution for a new observation x_* will be

$$p(x_*|\mathbf{X}) = \int p(x_*|\mu)p(\mu|\mathbf{X})d\mu = \int \mathcal{N}(x_*|\mu,\sigma^2)\mathcal{N}(\mu|\mu_N,\sigma_N^2)d\mu = \mathcal{N}(x_*|\mu_N, \sigma_N^2+\sigma^2)$$

- Note that, in contrast, the plug-in predictive posterior, given a point estimate $\hat{\mu}$ would be

$$p(x_*|\mathbf{X}) = \int p(x_*|\mu)p(\mu|\mathbf{X})d\mu \approx p(x_*|\hat{\mu})$$

Another Example: Estimating Gaussian Mean

- The posterior distribution for the unknown mean parameter μ

$$p(\mu|\mathbf{X}) = \frac{p(\mathbf{X}|\mu)p(\mu)}{p(\mathbf{X})} \quad \propto \quad \prod_{n=1}^{N} \exp\left[-\frac{(x_n-\mu)^2}{2\sigma^2}\right] \times \exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right]$$

- (Verify) The above posterior turns out to be another Gaussian $p(\mu|\mathbf{X}) = \mathcal{N}(\mu|\mu_N, \sigma_N^2)$ where

$$\frac{1}{\sigma_N^2} = \frac{N}{\sigma^2} + \frac{1}{\sigma_0^2}$$

$$\mu_N = \frac{\sigma^2}{N\sigma_0^2+\sigma^2}\mu_0 + \frac{N\sigma_0^2}{N\sigma_0^2+\sigma^2}\bar{x} \qquad \left(\text{where } \bar{x} = \frac{\sum_{n=1}^{N} x_n}{N}\right)$$

- Making prediction: The posterior predictive distribution for a new observation x_* will be

$$p(x_*|\mathbf{X}) = \int p(x_*|\mu)p(\mu|\mathbf{X})d\mu = \int \mathcal{N}(x_*|\mu,\sigma^2)\mathcal{N}(\mu|\mu_N,\sigma_N^2)d\mu = \mathcal{N}(x_*|\mu_N, \sigma_N^2+\sigma^2)$$

- Note that, in contrast, the plug-in predictive posterior, given a point estimate $\hat{\mu}$ would be

$$p(x_*|\mathbf{X}) = \int p(x_*|\mu)p(\mu|\mathbf{X})d\mu \approx p(x_*|\hat{\mu}) = \mathcal{N}(x_*|\hat{\mu},\sigma^2)$$