

Statistical Models & Computing Methods

Lecture 1: Introduction



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School of Mathematical Sciences, Peking University

September 08, 2025

- ▶ Class times:
 - ▶ Monday 3:10-5:00pm, Even Wednesday 10:10-12:00pm
 - ▶ Classroom Building No.3, Room 107
- ▶ Instructor:
 - ▶ Cheng Zhang: `chengzhang@math.pku.edu.cn`
- ▶ Teaching assistants:
 - ▶ Shiyue Zhang: `zhangshiyue@stu.pku.edu.cn`
 - ▶ Longlin Yu: `llyu@pku.edu.cn`
- ▶ Tentative office hours:
 - ▶ 315 Building No.20
 - ▶ Thursday 3:00-5:00pm or by appointment
- ▶ Website:
`https://zcrabbit.github.io/courses/smcm-f25.html`



- ▶ A branch of mathematical sciences focusing on efficient numerical methods for statistically formulated problems
- ▶ The focus lies on computer intensive statistical methods and efficient modern statistical models.
- ▶ Developing rapidly, leading to a broader concept of computing that combines the theories and techniques from many fields within the context of statistics, mathematics and computer sciences.



- ▶ Become familiar with a variety of modern computational statistical techniques and knows more about the role of computation as a tool of discovery
- ▶ Develop a deeper understanding of the mathematical theory of computational statistical approaches and statistical modeling.
- ▶ Understand what makes a good model for data.
- ▶ Be able to analyze datasets using a modern programming language (e.g., python).

- ▶ No specific textbook required for this course
- ▶ Recommended textbooks:
 - ▶ Givens, G. H. and Hoeting, J. A. (2005) Computational Statistics, 2nd Edition, Wiley-Interscience.
 - ▶ Gelman, A., Carlin, J., Stern, H., and Rubin, D. (2003). Bayesian Data Analysis, 2nd Edition, Chapman & Hall.
 - ▶ Liu, J. (2001). Monte Carlo Strategies in Scientific Computing, Springer-Verlag.
 - ▶ Lange, K. (2002). Numerical Analysis for Statisticians, Springer-Verlag, 2nd Edition.
 - ▶ Hastie, T., Tibshirani, R. and Friedman, J. (2009). The Elements of Statistical Learning, 2nd Edition, Springer.
 - ▶ Goodfellow, I., Bengio, Y. and Courville, A. (2016). Deep Learning, MIT Press.



- ▶ Optimization Methods
 - ▶ Gradient Methods
 - ▶ Expectation Maximization
- ▶ Approximate Bayesian Inference Methods
 - ▶ Markov chain Monte Carlo
 - ▶ Variational Inference
 - ▶ Scalable Approaches
- ▶ Applications in Machine Learning & Related Fields
 - ▶ Variational Autoencoder
 - ▶ Generative Adversarial Networks
 - ▶ Flow-based Generative Models
 - ▶ Bayesian Phylogenetic Inference



Familiar with at least one programming language (with python preferred!).

- ▶ All class assignments will be in python (and use numpy).
- ▶ You can find a good Python tutorial at

<http://www.scipy-lectures.org/>

You may find a shorter python+numpy tutorial useful at

<http://cs231n.github.io/python-numpy-tutorial/>

Familiar with the following subjects

- ▶ Probability and Statistical Inference
- ▶ Stochastic Processes



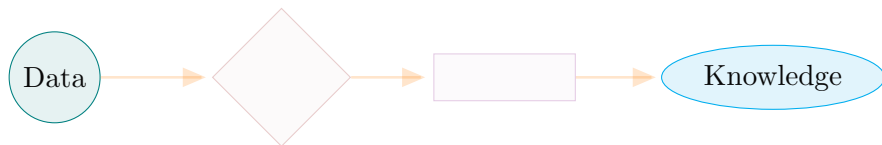
- ▶ 4 Problem Sets: $4 \times 15\% = 60\%$
- ▶ Final Course Project: 40%
 - ▶ up to 4 people for each team
 - ▶ Teams should be formed by the end of week 4
 - ▶ Midterm proposal: 5%
 - ▶ Oral presentation: 10%
 - ▶ Final write-up: 25%
- ▶ Late policy
 - ▶ 7 free late days, use them in your ways
 - ▶ Afterward, 25% off per late day
 - ▶ No more than 3 late days per PS
 - ▶ Does not apply to Final Course Project
- ▶ Collaboration policy
 - ▶ Finish your work independently, verbal discussion allowed

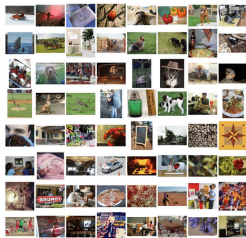


- ▶ Structure your project exploration around a general problem type, algorithm, or data set, but should explore around your problem, testing thoroughly or comparing to alternatives.
- ▶ Present a project proposal that briefly describe your teams' project concept and goals in one slide in class on 11/10.
- ▶ There will be in class project presentation at the end of the term. Not presenting your projects will be taken as voluntarily giving up the opportunity for the final write-ups.
- ▶ Turn in a write-up (< 10 pages) describing your project and its outcomes, similar to a research-level publication.

- ▶ A brief overview of statistical approaches
- ▶ Basic concepts in statistical computing





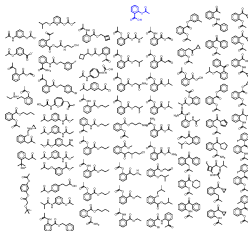


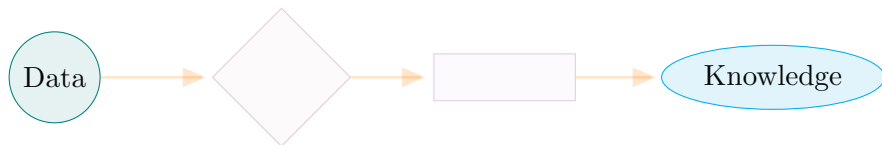
Data

In fact, the [redacted] market has five [redacted] most influential names of the retail and tech space - [redacted] and [redacted] collectively topped as [redacted] and is betting big in the global [redacted] in retail industry space. The [redacted] giants which are claimed to have a cut-throat competition with the [redacted] in terms of resources and capital are positioning themselves to become the future [redacted] platform. The trio is also expanding in other [redacted] and is looking heavily in the [redacted] based [redacted] to leverage the power of [redacted].

Backed by such powerful initiatives and presence of these conglomerates, the market in APAC is forecasted to be the fastest-growing [redacted] with an anticipated [redacted] over [redacted].

To further elaborate on the geographical trends, [redacted] has secured [redacted] of the global share in [redacted] and has been leading the regional landscape of [redacted] in the retail market. The [redacted] has a significant [redacted] in the regional trends with [redacted] of investments (including [redacted] private equity and venture capital) in artificial intelligence technology. Additionally, the region is a huge hub for startups in tandem with the presence of tech titans, with [redacted] and [redacted].



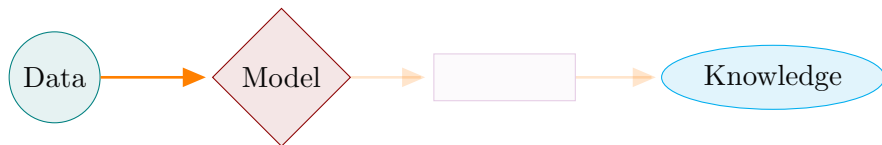
 $\mathcal{D}$ 

Linear Models

Neural Networks

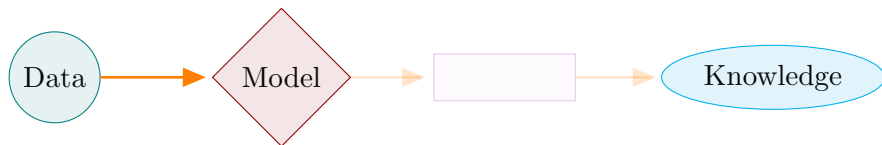
Bayesian Nonparametric Models

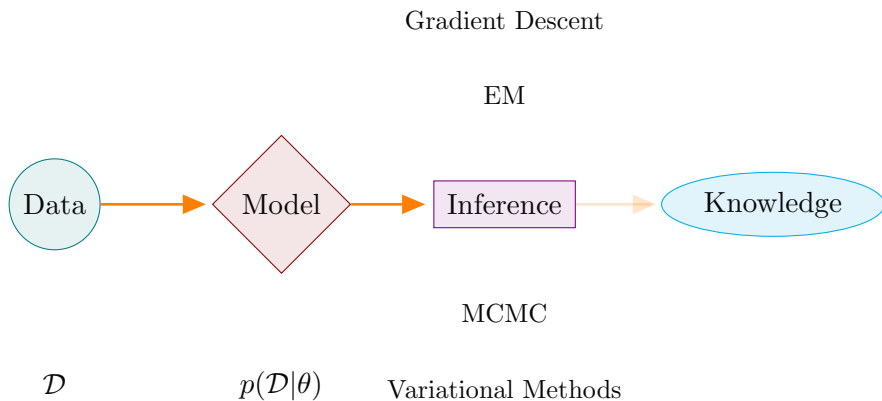
Generalized Linear Models

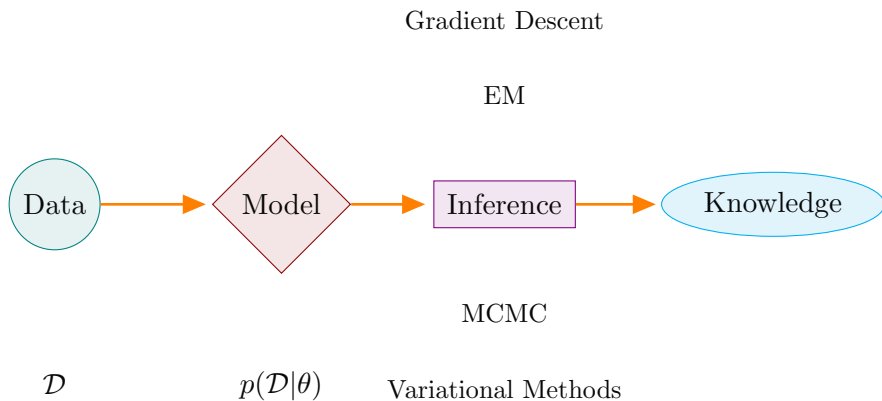


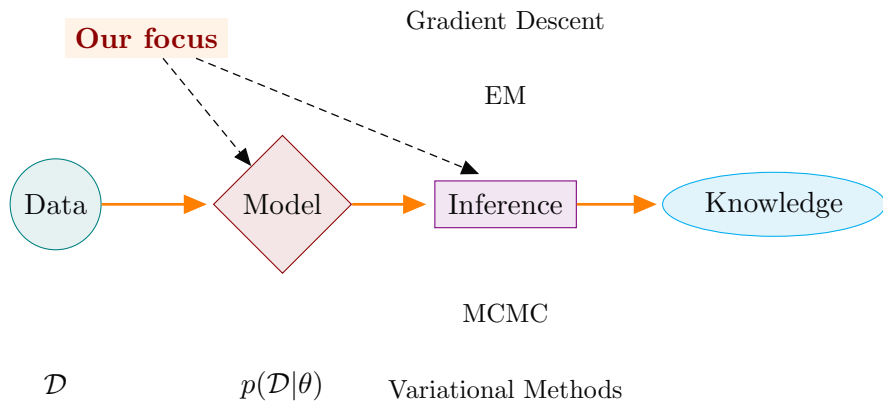
$\mathcal{D}$



 $\mathcal{D}$ $p(\mathcal{D}|\theta)$ 







“All models are wrong, but some are useful.”

George E. P. Box

Models are used to describe the data generating process, hence prescribe the probabilities of the observed data $\mathcal{D}$

$$p(\mathcal{D}|\theta)$$

also known as the **likelihood**.

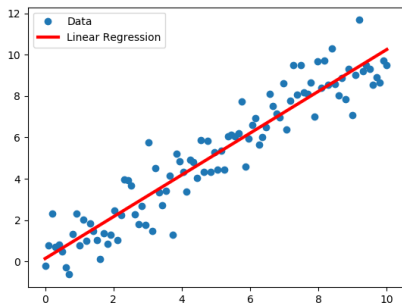


Data: $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^n$

Model:

$$Y = X\theta + \epsilon, \epsilon \sim \mathcal{N}(0, \sigma^2 I_n)$$

$$\Rightarrow Y \sim \mathcal{N}(X\theta, \sigma^2 I_n)$$



$$p(Y|X, \theta) = (2\pi\sigma^2)^{-n/2} \exp\left(-\frac{\|Y - X\theta\|_2^2}{2\sigma^2}\right)$$



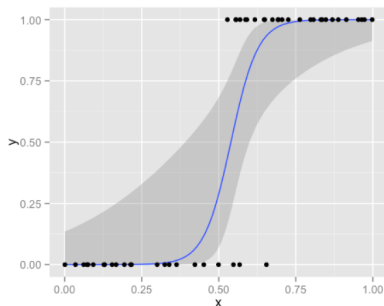
Data:

$$\mathcal{D} = \{(x_i, y_i)\}_{i=1}^n, y_i \in \{0, 1\}$$

Model:

$$Y \sim \text{Bernoulli}(p)$$

$$p = \frac{1}{1 + \exp(-X\theta)}$$



$$p(Y|X, \theta) = \prod_{i=1}^n p_i^{y_i} (1 - p_i)^{1-y_i}$$

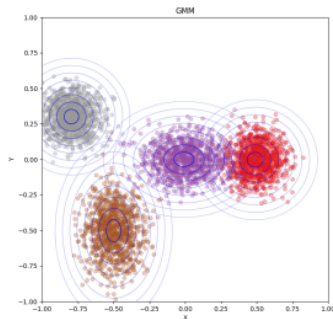


Data: $\mathcal{D} = \{y_i\}_{i=1}^n, y_i \in \mathbb{R}^d$

Model:

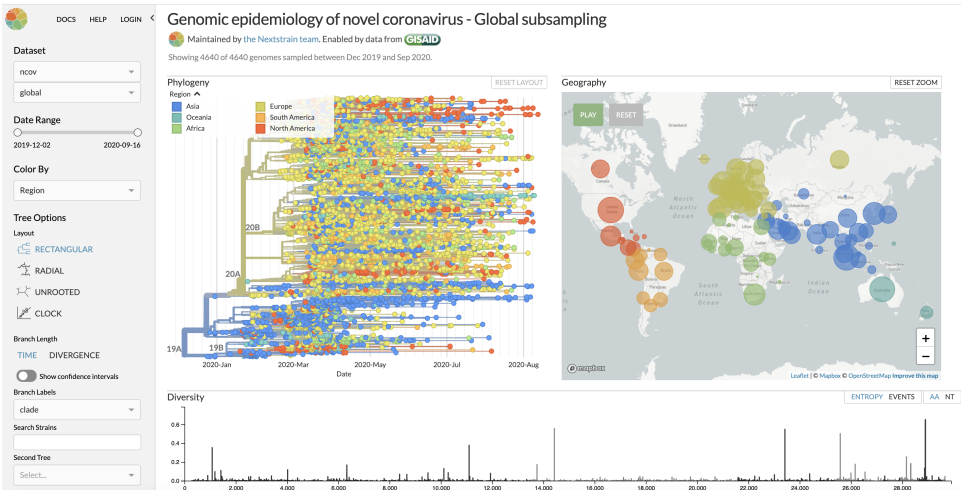
$$y|Z = z \sim \mathcal{N}(\mu_z, \sigma_z^2 I_d)$$

$$Z \sim \text{Categorical}(\alpha)$$



$$p(Y|\mu, \sigma, \alpha) = \prod_{i=1}^n \sum_{k=1}^K \alpha_k (2\pi\sigma_k^2)^{(-d/2)} \exp\left(-\frac{\|y_i - \mu_k\|_2^2}{2\sigma_k^2}\right)$$





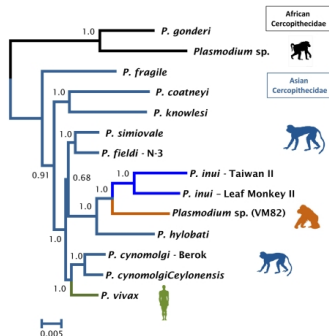
Data: DNA sequences $\mathcal{D} = \{y_i\}_{i=1}^n$

CTTTTC AAGG	AGTATT TCCT	ATGAAC GAGT	TAGACGG CAT
CATTGC AAAG	GGAA TAATCT	ATGAAC GCAA	TAATTAT TGA
CATTTTC AGG	ATAACT TTCT	ATGAAAG TAA	ACTTAAT ACT
GAAAAG AAAAT	CGAGGC AAAA	ATGAGC AAAAG	TCAGACT CGC
TGCAAAAAA A	GGAGAC CAT	ATGCTTG ACG	CTCAAAC CAT
TTTTTG TGG A	GAAGAC GCGT	GTGATT GTTA	AACGACC CGT
GTTATT AAGG	ATATGT TCAT	ATGTTTT TC A	AAAAGA ACCT
TACCCAC CGG	ATTTT ACCT	ATGCTC ACCG	TTAAGC AGAT
AATCAAA ATG	GAATAA ATC	ATGCTAC CAT	CTATTT CAAT
ATCACAG GGG	AAGGTG AGAT	ATGCACT CTC	AAATCT GGGT
ACATCC AGTG	AGAGAG ACCG	ATGCAT CCGA	TGCTGA ACAT



Data: DNA sequences $\mathcal{D} = \{y_i\}_{i=1}^n$

CTTTTCAAGG	AGTATTTTCCT	ATGAACGAGT	TAGACGGCAT
CATTGCAAAAG	GGAATAATCT	ATGAACGCAA	TAATTATTGA
CATTTTCAGG	ATAACTTTCT	ATGAAAGTAA	ACTTAATACT
GAAAAGAAAAT	CGAGGCAAAA	ATGAGCAAAG	TCAGACTCGC
TGCAAAAAA	GGAGACCAT	ATGCTTGACG	CTCAAACCAT
TTTTTGTGGA	GAAGACGCGT	GTGATTGTTA	AACGACCCGT
GTTATTAAGG	ATATGTTTCAT	ATGTTTTTCA	AAAAGAACCT
TACCCACCGG	ATTTTTACCC	ATGCTCACCG	TTAAGCAGAT
AATCAAAATG	GAATAAAATC	ATGCTACCAT	CTATTTCAAT
ATCACAGGGG	AAGGTGAGAT	ATGCACTCTC	AAATCTGGGT
ACATCCAGTG	AGAGAGACCG	ATGCATCCGA	TGCTGAACAT



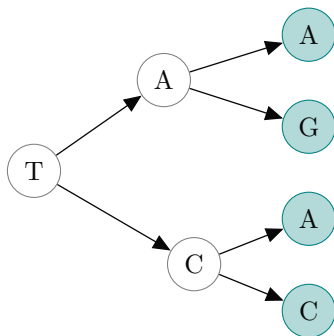
Data: DNA sequences $\mathcal{D} = \{y_i\}_{i=1}^n$

Model: Phylogenetic tree: (τ, q) .

Substitution model:

- ▶ stationary distribution: $\eta(a_\rho)$.
- ▶ transition probability:

$$p(a_u \rightarrow a_v | q_{uv}) = P_{a_u a_v}(q_{uv})$$



Data: DNA sequences $\mathcal{D} = \{y_i\}_{i=1}^n$

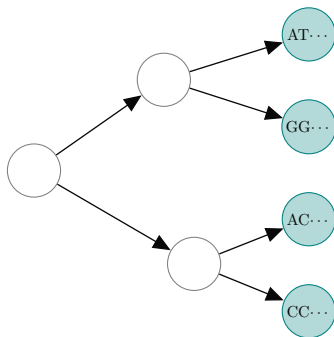
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$$p(a_u \rightarrow a_v | q_{uv}) = P_{a_u a_v}(q_{uv})$$

$$p(Y|\tau, q) = \prod_{i=1}^n \sum_{a^i} \eta(a_\rho^i) \prod_{(u,v) \in E(\tau)} P_{a_u^i a_v^i}(q_{uv})$$



Data: DNA sequences $\mathcal{D} = \{y_i\}_{i=1}^n$

Model: Phylogenetic tree: (τ, q) .

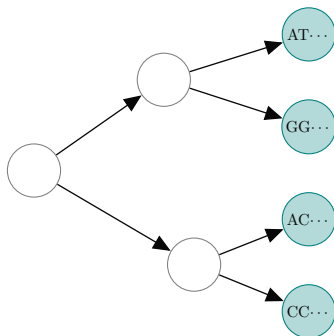
Substitution model:

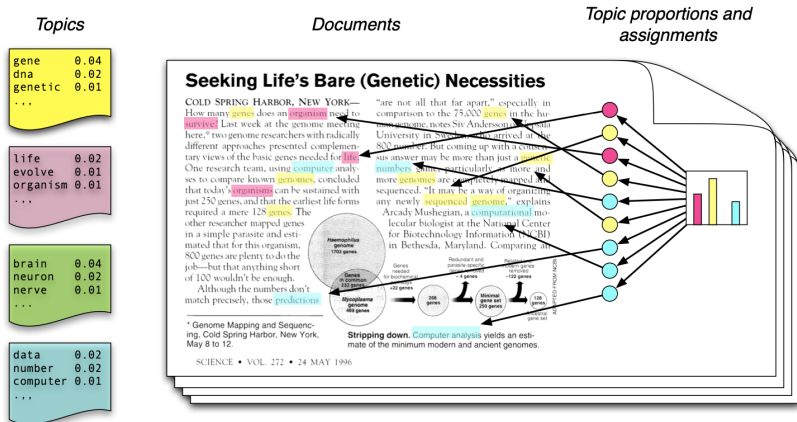
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where a^i agree with y_i at the tips

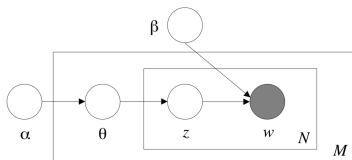




- Each topic is a distribution over words
- Documents exhibit multiple topics



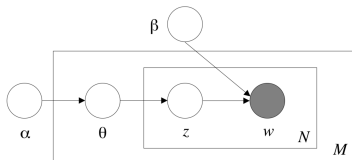
Data: a corpus $\mathcal{D} = \{\mathbf{w}_i\}_{i=1}^M$



Model: for each document $\mathbf{w}$ in $\mathcal{D}$,



Data: a corpus $\mathcal{D} = \{\mathbf{w}_i\}_{i=1}^M$

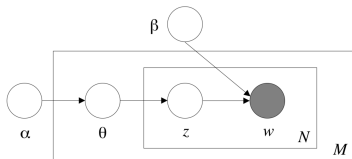


Model: for each document $\mathbf{w}$ in $\mathcal{D}$,

- choose a mixture of topics $\theta \sim \text{Dir}(\alpha)$



Data: a corpus $\mathcal{D} = \{\mathbf{w}_i\}_{i=1}^M$



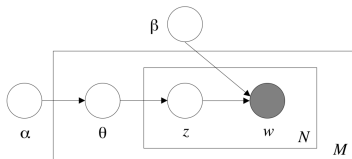
Model: for each document $\mathbf{w}$ in $\mathcal{D}$,

- ▶ choose a mixture of topics $\theta \sim \text{Dir}(\alpha)$
- ▶ for each of the N words w_n ,

$$z_n \sim \text{Multinomial}(\theta), \quad w_n | z_n, \beta \sim p(w_n | z_n, \beta)$$



Data: a corpus $\mathcal{D} = \{\mathbf{w}_i\}_{i=1}^M$



Model: for each document $\mathbf{w}$ in $\mathcal{D}$,

- ▶ choose a mixture of topics $\theta \sim \text{Dir}(\alpha)$
- ▶ for each of the N words w_n ,

$$z_n \sim \text{Multinomial}(\theta), \quad w_n | z_n, \beta \sim p(w_n | z_n, \beta)$$

$$p(\mathcal{D} | \alpha, \beta) = \prod_{d=1}^M \int p(\theta_d | \alpha) \prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn} | \theta_d) p(w_{dn} | z_{dn}, \beta) d\theta_d$$



Many well-known distributions take the following form

$$p(y|\theta) = h(y) \exp(\phi(\theta) \cdot T(y) - A(\theta))$$

- ▶ $\phi(\theta)$: natural/canonical parameters
- ▶ $T(y)$: sufficient statistics
- ▶ $A(\theta)$: log-partition function

$$A(\theta) = \log \left(\int_y h(y) \exp(\phi(\theta) \cdot T(y)) dy \right)$$



$Y \sim \text{Bernoulli}(\theta)$:

$$\begin{aligned} p(y|\theta) &= \theta^y (1 - \theta)^{1-y} \\ &= \exp \left(\log \left(\frac{\theta}{1 - \theta} \right) y + \log(1 - \theta) \right) \end{aligned}$$

- ▶ $\phi(\theta) = \log \left(\frac{\theta}{1 - \theta} \right)$
- ▶ $T(y) = y$
- ▶ $A(\theta) = -\log(1 - \theta) = \log(1 + e^{\phi(\theta)})$
- ▶ $h(y) = 1$



$Y \sim \mathcal{N}(\mu, \sigma^2)$:

$$\begin{aligned} p(y|\mu, \sigma^2) &= \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2\sigma^2}(y - \mu)^2\right) \\ &= \frac{1}{\sqrt{2\pi}} \exp\left(\frac{\mu}{\sigma^2}y - \frac{1}{2\sigma^2}y^2 - \frac{\mu^2}{2\sigma^2} - \log \sigma\right) \end{aligned}$$

- ▶ $\phi(\theta) = [\frac{\mu}{\sigma^2}, -\frac{1}{2\sigma^2}]^T$
- ▶ $T(y) = [y, y^2]^T$
- ▶ $A(\theta) = \frac{\mu^2}{2\sigma^2} + \log \sigma$
- ▶ $h(y) = \frac{1}{\sqrt{2\pi}}$



$Y = \{y_i\}_{i=1}^n$, $y_i \sim p(y_i|\theta)$, the Log-likelihood

$$L(\theta; Y) = \sum_{i=1}^n \log p(y_i|\theta)$$

The gradient of L with respect to θ is called the **score**

$$s(\theta) = \frac{\partial L}{\partial \theta}$$

The expected value of the score is zero

$$\mathbb{E}(s) = \sum_{i=1}^n \int \frac{\partial \log p(y_i|\theta)}{\partial \theta} p(y_i|\theta) dy_i = \sum_{i=1}^n \frac{\partial}{\partial \theta} \int p(y_i|\theta) dy_i = 0$$



Fisher information is the variance of the score.

$$\mathcal{I}(\theta) = \mathbb{E}(ss^T)$$

Under mild assumptions (e.g., exponential families),

$$\mathcal{I}(\theta) = -\mathbb{E} \left(\frac{\partial^2 L}{\partial \theta \partial \theta^T} \right)$$

Intuitively, **Fisher information** is a measure of the **curvature** of the Log-likelihood function. Therefore, it reflects the sensitivity of model about the parameter at its current value.



- Kullback-Leibler (KL) divergence is a measure of statistical distance between two distributions $p(x)$ and $q(x)$

$$D_{KL}(q||p) = \int q(x) \log \frac{q(x)}{p(x)} dx$$

- KL divergence is non-negative

$$D_{KL}(q||p) = - \int q(x) \log \frac{p(x)}{q(x)} \geq - \log \int p(x) dx = 0$$

- Consider a family of distributions $p(x|\theta)$, Fisher information is Hessian of KL-divergence between two distributions $p(x|\theta)$ and $p(x|\theta')$ with respect to θ' at $\theta' = \theta$

$$\nabla_{\theta'}^2 D_{KL}(p(x|\theta)||p(x|\theta'))|_{\theta'=\theta} = \mathcal{I}(\theta)$$



$$\begin{aligned}\hat{\theta}_{MLE} &= \arg \max_{\theta} L(\theta) \approx \arg \max_{\theta} \mathbb{E}_{y \sim p_{data}} \log \frac{p(y|\theta)}{p_{data}(y)} \\ &= \arg \min_{\theta} D_{KL}(p_{data}(y) || p(y|\theta))\end{aligned}$$

- **Consistency.** Under weak regularity condition, $\hat{\theta}_{MLE}$ is consistent: $\hat{\theta}_{MLE} \rightarrow \theta_0$ in probability as $n \rightarrow \infty$, where θ_0 is the “true” parameter
- **Asymptotical Normality.**

$$\hat{\theta}_{MLE} - \theta_0 \rightarrow \mathcal{N}(0, \mathcal{I}^{-1}(\theta_0))$$

See Rao 1973 for more details.



$$L(\theta; y_1, \dots, y_n) = \sum_{i=1}^n y_i \log \theta - n\theta - \sum_{i=1}^n \log y_i!$$

$$s(\theta) = \frac{\sum_{i=1}^n y_i}{\theta} - n, \quad \mathcal{I}(\theta) = \frac{n}{\theta}$$

$$\hat{\theta}_{MLE} = \arg \max_{\theta} \sum_{i=1}^n y_i \log \theta - n\theta = \frac{\sum_{i=1}^n y_i}{n}$$

By the **Law of large numbers**

$$\hat{\theta}_{MLE} \xrightarrow{p} \theta_0$$

By **central limit theorem**

$$\hat{\theta}_{MLE} - \theta_0 \xrightarrow{d} \mathcal{N}\left(0, \frac{\theta_0}{n}\right)$$



- ▶ Can we find an unbiased estimator with smaller variance than $\mathcal{I}^{-1}(\theta_0)$?
- ▶ **Cramér-Rao Lower Bound:** For any unbiased estimator $\hat{\theta}$ of θ_0 based on independent observations following the true distribution, the variance of the estimator is bounded by the reciprocal of the Fisher information

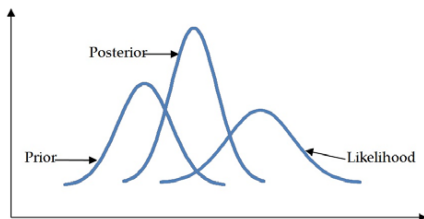
$$\text{Var}(\hat{\theta}) \geq \frac{1}{\mathcal{I}(\theta_0)}$$

- ▶ Sketch of proof: Consider a general estimator $T = t(X)$ with $\mathbb{E}(T) = \psi(\theta_0)$. Let s be the score function,

$$\text{Cov}(T, s) = \mathbb{E}(Ts) = \psi'(\theta_0) \Rightarrow \text{Var}(T) \geq \frac{[\psi'(\theta_0)]^2}{\text{Var}(s)} = \frac{[\psi'(\theta_0)]^2}{\mathcal{I}(\theta_0)}$$



In Bayesian statistics, besides specifying a model $p(y|\theta)$ for the observed data, we also specify our **prior** $p(\theta)$ for the model parameters.



Bayes rule for inverse probability

$$p(\theta|\mathcal{D}) = \frac{p(\mathcal{D}|\theta) \cdot p(\theta)}{p(\mathcal{D})} \propto p(\mathcal{D}|\theta) \cdot p(\theta)$$

known as the **posterior**.



- uncertainty quantification, provides more useful information
- reducing overfitting. **Regularization $\iff$ Prior.**

Prediction

$$p(x|\mathcal{D}) = \int p(x|\theta, \mathcal{D})p(\theta|\mathcal{D})d\theta$$

Model Comparison

$$p(m|\mathcal{D}) = \frac{p(\mathcal{D}|m)p(m)}{p(\mathcal{D})}$$

$$p(\mathcal{D}|m) = \int p(\mathcal{D}|\theta, m)p(\theta|m) d\theta$$



- ▶ **Subjective Priors.** Priors should reflect our beliefs as well as possible. They are subjective, but not arbitrary.
- ▶ **Hierarchical Priors.** Priors of multiple levels.

$$\begin{aligned} p(\theta) &= \int p(\theta|\alpha)p(\alpha) d\alpha \\ &= \int p(\theta|\alpha) d\alpha \int p(\alpha|\beta)p(\beta) d\beta \end{aligned}$$

- ▶ **Conjugate Priors.** Priors that ease computation, often used to facilitate the development of inference and parameter estimation algorithms.



- ▶ **Conjugacy:** prior $p(\theta)$ and posterior $p(\theta|Y)$ belong to the same family of distribution
- ▶ Exponential family

$$p(Y|\theta) \propto \exp \left(\phi(\theta) \cdot \sum_i T(y_i) - nA(\theta) \right)$$

- ▶ Conjugate prior

$$p(\theta) \propto \exp (\phi(\theta) \cdot \nu - \eta A(\theta))$$

- ▶ Posterior

$$p(\theta|Y) \propto \exp \left(\phi(\theta) \cdot (\nu + \sum_i T(y_i)) - (n + \eta)A(\theta) \right)$$



Data: $\mathcal{D} = \{\mathbf{x}_i\}_{i=1}^m$. For each $\mathbf{x}$ in $\mathcal{D}$

$$p(\mathbf{x}|\theta) \propto \exp \left(\sum_{k=1}^K x_k \log \theta_k \right)$$

Use $\text{Dir}(\alpha)$ as the **conjugate** prior

$$p(\theta) \propto \exp \left(\sum_{k=1}^K (\alpha_k - 1) \log \theta_k \right)$$

$$p(\theta|\mathcal{D}) \propto \exp \left(\sum_{k=1}^K \left(\alpha_k - 1 + \sum_{i=1}^M x_{ik} \right) \log \theta_k \right)$$



Consider random variables $\{X_t\}, t = 0, 1, \dots$ with state space $\mathcal{S}$

Markov Property

$$p(X_{n+1} = x | X_0 = x_0, \dots, X_n = x_n) = p(X_{n+1} = x | X_n = x_n)$$

Transition Probability

$$P_{ij}^n = p(X_{n+1} = j | X_n = i), \quad i, j \in \mathcal{S}.$$

A Markov chain is called *time homogeneous* if $P_{ij}^n = P_{ij}, \forall n$.

A Markov chain is governed by its transition probability matrix.



- Stationary Distribution.

$$\pi^T P = \pi^T.$$

- Ergodic Theorem. If the Markov chain is irreducible and aperiodic, with stationary distribution π , then

$$X_n \xrightarrow{d} \pi$$

and for any function h

$$\frac{1}{n} \sum_{t=1}^n h(X_t) \rightarrow \mathbb{E}_{\pi} h(X), \quad n \rightarrow \infty$$

given $\mathbb{E}_{\pi}|h(X)|$ exists.



- ▶ In general, finding MLE and posterior analytically is difficult. We almost always have to resort to computational methods.
- ▶ In this course, we'll discuss a variety of computational techniques for numerical optimization and integration, approximate Bayesian inference methods, with applications in statistical machine learning, computational biology and other related field.



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