

An introduction to Stein's method

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Three lectures

1. Basics and normal approximation
2. Poisson approximation
3. Multivariate and process approximation

References:

- ▶ Ross (2011). Fundamentals of Stein's method. *Probability Surveys*.
- ▶ Barbour, Holst, Janson (1992). Poisson approximation.
- ▶ Chen, Goldstein, Shao (2011). Normal approximation by Stein's method.

An introduction to Stein's method

1. Basics and normal approximation

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Classical CLT

Assume

- ▶ X_1, X_2, \dots iid,
- ▶ $\mathbb{E}X_i = 0, \text{Var}(X_i) = 1,$
- ▶ $W = W_n = \frac{1}{\sqrt{n}} \sum_{i=1}^n X_i.$

Then, for $Z \sim \text{Normal}(0, 1)$ and $x \in \mathbb{R},$

$$\mathbb{P}(W_n \leq x) \rightarrow \mathbb{P}(Z \leq x).$$

Berry-Esseen Theorem

Assume

- ▶ X_1, X_2, \dots iid,
- ▶ $\mathbb{E}X_i = 0$, $\text{Var}(X_i) = 1$, and $\mathbb{E}[|X_i|^3] < \infty$,
- ▶ $W = W_n = \frac{1}{\sqrt{n}} \sum_{i=1}^n X_i$.

Then, for $Z \sim \text{Normal}(0, 1)$ and $x \in \mathbb{R}$,

$$|\mathbb{P}(W_n \leq x) - \mathbb{P}(Z \leq x)| \leq \frac{\mathbb{E}[|X_1|^3]}{\sqrt{n}}.$$

Dependency Graph

We say X_1, X_2, \dots, X_n has **dependency graph** G with vertices $\{1, \dots, n\}$ if

- ▶ for any two disjoint subsets $\{i_1, \dots, i_k\}$ and $\{j_1, \dots, j_m\}$ of vertices, with no edges between the two sets,

$(X_{i_1}, \dots, X_{i_k})$ is independent of $(X_{j_1}, \dots, X_{j_m})$.

Q: Under what conditions on G is $\sum_{i=1}^n X_i$ close in distribution to a normal distribution?

Sleight of Hand

For random variables W and Z , define the **Wasserstein distance** between their distributions by

$$d_{\text{Lip}}(W, Z) = \sup_{h \in \text{Lip}_1} |\mathbb{E}h(W) - \mathbb{E}h(Z)|.$$

Proposition: If Z has density bounded by C , then

$$|\mathbb{P}(W \leq x) - \mathbb{P}(Z \leq x)| \leq \sqrt{(2C)d_{\text{Lip}}(W, Z)}.$$

Stein's Method Framework

Three steps to Stein's method for a given target distribution of Z .

1. Characterizing operator $\mathcal{A} = \mathcal{A}_Z$ on real valued functions:

$$\mathbb{E}\mathcal{A}f(X) = 0 \text{ wide class of functions } f \iff X \stackrel{d}{=} Z.$$

2. For given h , find Stein solution f_h :

$$\mathcal{A}f_h(x) = h(x) - \mathbb{E}h(Z) =: \tilde{h}(x).$$

3. Use structure of W and properties of f_h to bound

$$|\mathbb{E}\mathcal{A}f_h(W)| = |\mathbb{E}h(W) - \mathbb{E}h(Z)|.$$

For bound on d_{Lip} , take $h \in \text{Lip}_1$.

Stein's Method for Normal Approximation

For random variable W and $Z \sim \text{Normal}(0, 1)$,

$$d_{\text{Lip}}(W, Z) \leq \sup_{f \in \mathcal{F}} |\mathbb{E}[f'(W) - Wf(W)]|,$$

where

$$\mathcal{F} := \left\{ f : \|f\|_{\infty} \leq 2; \|f''\|_{\infty} \leq 2; \|f'\|_{\infty} \leq \sqrt{2/\pi} \right\}.$$

Dependency Graph Bound

Assume

- ▶ X_1, X_2, \dots, X_n has dependency graph with maximum degree bounded above by D .
- ▶ $\mathbb{E}X_i = 0$ and $\mathbb{E}[X_i^4] < \infty$.
- ▶ $W = \frac{1}{\sigma} \sum_{i=1}^n X_i$, where $\sigma^2 = \text{Var} \left(\sum_{i=1}^n X_i \right)$.

Then, for $Z \sim \text{Normal}(0, 1)$,

$$d_{\text{Lip}}(W, Z) \leq 3(D + 1)^2 \left(\frac{1}{\sigma^3} \sum_{i=1}^n \mathbb{E}[|X_i|^3] + \frac{1}{\sigma^2} \sqrt{\sum_{i=1}^n \mathbb{E}[X_i^4]} \right).$$

Exercises

- ▶ (Easy) Apply the previous result directly to W equal to the (centered and scaled) number of triangles in an Erdős-Rényi random graph with m vertices and edge probability p , to derive a CLT for $p = p_m \asymp m^{-\alpha}$ for $0 \leq \alpha < 2/9$.
- ▶ (Hard) In the setting of the previous exercise, derive a CLT in a greater range of α by bounding $|\mathbb{E}[f'(W) - Wf(W)]|$ directly using additional structure of W and Taylor expansion.

References and Further Reading

Basic introduction:

- ▶ Ross (2011). Fundamentals of Stein's method. *Probability Surveys*. **Sections 1, 2, 3.1 and 3.2.**

Research monograph:

- ▶ Chen, Goldstein, Shao (2011). Normal approximation by Stein's method. **Sections 1.3, 2.1, 2.2, 4.7.**