Beamer Example

eqs

April 8, 2021

About this Beamer project

- This template is available for both Japanese and English.
- 日本語と英語のどっちのプレゼンでも使えます.

Commands for brackets in equations

- `\nbracket`: `\left( ... \right)`

$$\lim_{x \to \infty} \left(1 + \frac{1}{x} \right)^x = e$$

- `\cbracket`: `\left\{ ... \right\}`

$$\frac{\beta}{2} \sum_{n=1}^{N} \left\{ t_n - \mathbf{w}^\top \boldsymbol{\phi}(\mathbf{x}_n) \right\}^2$$

- `\rbracket`: `\left[ ... \right]`
- `\abracket`: `\left\langle ... \right\rangle`

Highlight Commands

- \highlight
- \highlightcap
- \highlightcaphead
- \highlightcapoverlay
- \highlightcapheadoverlay

Example Slides

Example 1 (highlight)

$$\begin{aligned} & x^2 - 6x + 2 \\ &= x^2 - 6x + 9 - 7 \\ &= (x-3)^2 - 7 \end{aligned}$$

Example 2 (`highlightcap`, `cbracket`)

When we consider a Gaussian prior $p(\mathbf{w}|\alpha) = \mathcal{N}(\mathbf{w}|\mathbf{0}, \alpha^{-1}\mathbf{I})$, maximization of the corresponding posterior $p(\mathbf{w}|\mathbf{t})$ with respect to $\mathbf{w}$ is equivalent to the minimization of

$$\frac{\beta}{2}\sum_{n=1}^{N}\left\{t_n - \mathbf{w}^\top \boldsymbol{\phi}(\mathbf{x}_n)\right\}^2 + \frac{\alpha}{2}\mathbf{w}^\top\mathbf{w} \qquad (3.55')$$

the minimization corresponds to (3.27) with $\lambda = \alpha/\beta$.

Example 2 (highlightcap, cbracket)

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$$\underbrace{\frac{\beta}{2}\sum_{n=1}^{N}\left\{t_n - \mathbf{w}^\top \boldsymbol{\phi}(\mathbf{x}_n)\right\}^2}_{\text{an error function}} + \frac{\alpha}{2}\mathbf{w}^\top\mathbf{w} \qquad (3.55')$$

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$$\underset{\text{an error function}}{\boxed{\frac{\beta}{2}\sum_{n=1}^{N}\left\{t_n - \mathbf{w}^\top \boldsymbol{\phi}(\mathbf{x}_n)\right\}^2}} + \underset{\text{a quadratic regularization}}{\boxed{\frac{\alpha}{2}\mathbf{w}^\top\mathbf{w}}} \tag{3.55'}$$

the minimization corresponds to (3.27) with $\lambda = \alpha/\beta$.

Example 3 (`highlightcapoverlay`)

For the moment, the noise precision β as a known constant.
Where the likelihood function of t is defined as:

$$p(\mathbf{t}|\mathbf{w}) = \prod_{n=1}^{N} \mathcal{N}(t_n|\mathbf{w}^\top \boldsymbol{\phi}(\mathbf{x}_n), \beta^{-1}) \tag{3.10'}$$

Example 3 (`highlightcapoverlay`)

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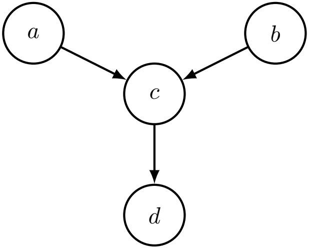
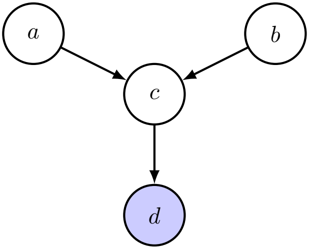
The exponential of a quadratic func. of $\mathbf{w}$

Example 4 (multi-columns)



- Item 1
- Item 2
- Item 3

Example 4 (multi-columns)



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