# 行政院國家科學委員會專題研究計畫 期末報告

## 貝氏方法在網路評分資料之應用(第 2 年)

計 畫 類 別 ： 個別型
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報 告 附 件 ： 出席國際會議研究心得報告及發表論文

公 開 資 訊 ： 本計畫可公開查詢

中 華 民 國 102 年 09 月 18 日

中 文 摘 要 ： 網路提供消費者大量資訊. 網路使用者對於各種產品,如電影,音樂,餐廳, 商品等給予的評分,常常構成相當大的網路資料. 關於這類評分資料,目前網路上常見的呈現方式是以各產品所獲得的平均評分表示(例如以五個星號代表五分). 然而,因為沒有考慮到評分者與評分者之間的差異,這樣簡單的平均分數有所缺失.

Ho and Quinn (2008) 提出一個貝氏模型 並以 MCMC 方法估計其中參數,該模型 納入評分者與評分者之間的差異,比平均分數能夠更合理的解釋評分資料. 可是, 如該二位作者所指出, 此方法之最大問題在於當資料量很大,甚至於當新資料進來而需要重新估計模型參數, 以 MCMC 方法來計算於實際應用上是不可行的.

本研究計畫提出一個有效可行的方法來解決這個問題. 應用在兩組實際數據,得到不錯結果.

中文關鍵詞： 貝氏方法,評分資料

英 文 摘 要 ： The internet has offered consumers with a vast amount of information. One growing area of such information is ratings by internet users on various kinds of products such as movies, music, restaurants, commodities, etc. The current displays of each product ‘s preference are typically based on ’ average rating,’ but the average rating method ignores systematic differences across raters.
Ho and Quinn (2008) proposed a Bayesian model and Markov chain Monte Carlo (MCMC) methods to take into account systematic differences across raters, and at the same time incorporate statistical uncertainty in the ratings. However, to work efficiently on an industrial scale and to adjust the parameters in real-time as new rating arrive, the MCMC methods may not be computationally feasible.
The current project provided a feasible solution to this problem by using efficient approximation algorithm. Experiments on two real datasets are promising.

英文關鍵詞： Bayesian method, ratings data

**A Statistical Analysis of Internet Ratings Data**

**final report**

# 1 Introduction

As the Internet population continue to grow, the ratings data generated by Internet users increase rapidly. The ratings data are typically ordinal measurements on the quality of all kinds of items such as movies, books, consumer products, etc. These data have provided much information for consumers to make product choices. For a given product, most of the current graphical displays provide the number of votes it receives and a number of stars to represent the mean rating. Some displays may also present the frequency plot of ratings.

However, typical ratings data exhibits systematic tendencies for some raters to give higher scores than others, and some may not discriminate very well between products. The current displays all ignore the systematic differences across raters.

Ho and Quinn [2] proposed to use a Bayesian item response theory (IRT) model for ratings data. Then, they fit the model using Markov Chain Monte Carlo (MCMC), and proposed graphical displays based on estimates of model parameters. This model can account for the rater bias, and the proposed graphical displays are easily interpretable and incorporate statistical uncertainty in the ratings. While the methodology is reasonable, it has not been used by any website. The main difficulty is that, as the Internet data grow rapidly and the new ratings continuously arrive, the MCMC methods may not be computationally feasible to adjust model parameters.

Some researchers have employed Bayesian IRT models in psychological and educational studies; for example, Patz and Junker [3], Fox and Glas [1], and Wang et al. [4]. They all rely on the MCMC approach.

The MCMC approach is a nondeterministic method for approximate Bayesian inference. This approach often gives more accurate inference, but requires considerably more computation. Alternatively, there are deterministic approaches such as Laplace method, variational Bayes, expectation propagation, among others. They are part of mainstream machine learning methodologies. For many applications, deterministic methods produce solutions of comparable accuracy to MCMC at greater speed. In fact, Ho and Quinn [2, Section 5] pointed out that their model-fitting approach (MCMC) needs to be modified so as to work efficiently on an industrial scale or real-time data.

The present paper extends the online Bayesian method in Weng and Lin [5] to the IRT model for ratings data. First, we obtain an efficient online algorithm to adjust the parameters in real-time as new ratings arrive. Secondly, the proposed method provides a reasonable alternative to MCMC approach.

## 2 Preliminaries

For the sake of being self-contained, we review the model-based approach in Ho and Quinn [2]. Suppose that there are $R$ raters and $P$ products. Let $y_{rp}$ be the rating of product $p$ by rater $r$, and $Y = [y_{rp}]$ the $R \times P$ rater-by-product matrix. Assume that $y_{rp}$ is ordinal and takes values in $\{1, 2, ..., C\}$, where larger numbers indicate higher preference. In many cases, $y_{rp}$ is not observed. It is sensible to introduce a missingness indicator $z_{rp}$ and assume that the data are generated according to

$$y_{rp}^{\text{obs}} = \begin{cases} c & \Leftrightarrow y_{rp}^* \in (\gamma_{c-1}, \gamma_c] \text{ and } z_{rp} = 0 \\ \text{missing} & \Leftrightarrow z_{rp} = 1 \end{cases} \tag{1}$$

where $y_{rp}^*$ is a latent variable and $\gamma_0 < \gamma_1 < \cdots < \gamma_C$ are cutpoints. Assume that $\gamma_0 = -\infty$, $\gamma_1 = 0$, and $\gamma_C = \infty$.

The latent variable $y_{rp}^*$ is parametrized as

$$y_{rp}^* = \alpha_r + \beta_r \theta_p + \epsilon_{rp},\ \epsilon_{rp} \overset{iid}{\sim} \mathcal{N}(0, 1),\ r \in R, p \in P. \tag{2}$$

The parameter $\alpha$ captures the center of rater $r$'s internal scale. For a more "critical" rater $r$, the $\alpha_r$ tends to be smaller. The parameter $\beta_r$ captures how well rater $r$ discriminates between low and high quality products. Ho and Quinn [2] constrained $\beta_r \in \Re^+ \ \forall r$ to identify the sign of $\theta_r$; otherwise, two different sets of parameter values can give the same model. A value of $\beta_r$ near 0 means that rater $r$ is unable to distinguish between low and high quality; a larger $\beta_r$ means that rater $r$ is discriminating. The parameter $\theta_p$ captures the latent quality of product $p$. With the constraint that $\beta_r \in \Re^+ \ \forall r$, the value of $y_{rp}^*$ is increasing in $\theta_p$; and the interpretation of $\theta_p$ is that quality is increasing in $\theta_p \ \forall p$.

$$P(\mathbf{Y}^{\text{obs}}|\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\theta},\boldsymbol{\gamma}) = \prod_{p,r:z_{rp}=0}\{\Phi(\gamma_{y_{rp}^{\text{obs}}} - \alpha_r - \beta_r\theta_p) - \Phi(\gamma_{y_{rp}^{\text{obs}}-1} - \alpha_r - \beta_r\theta_p)\}, \quad (3)$$

where $\gamma_{y_{rp}^{obs}} = \gamma_c \Leftrightarrow y_{rp}^{obs} = c$. The prior distribution for the parameters are assumed as follows: $\alpha_r \overset{iid}{\sim} \mathcal{N}(1,1)$, $\beta_r \overset{iid}{\sim} \mathcal{N}(-5,20)$ truncated to the positive half, $\gamma \overset{iid}{\sim}$ improper uniform, $\theta_p \overset{iid}{\sim} \mathcal{N}(0,1)$. Given $M$ Markov Chain Monte Carlo samples $\{\alpha_r^{(m)}, \beta_r^{(m)}, \theta_p^{(m)}, \gamma^{(m)}\}_{m=1}^M$ from the posterior distribution $p(\alpha_r, \beta_r, \theta_p, \gamma|\mathbf{Y}^{obs})$, the posterior predictive density for $y_{rp}$ can be approximated with:

$$\begin{aligned} & \mathrm{P}(y_{rp}^{rep} = c|\mathbf{Y}^{obs}) \\ \approx\ & \frac{1}{M}\sum_{m=1}^{M}\{\Phi(\gamma_c^{(m)} - \alpha_r^{(m)} - \beta_r^{(m)}\theta_p^{(m)}) - \Phi(\gamma_{c-1}^{(m)} - \alpha_r^{(m)} - \beta_r^{(m)}\theta_p^{(m)})\} \end{aligned} \quad (4)$$

for $c = 1, ..., C$. Their proposed graphical displays depend on the posterior predictive probabilities for product $p$ over all raters:

$$\tau_{pc} = \frac{1}{|R|}\sum_{r\in R} P(y_{rp}^{rep} = c|\mathbf{Y}^{obs}) \quad (5)$$

# 3 Main results

We propose to estimate $\tau_{pc}$ by

$$P(y_{pr} = c|Y^{\text{obs}}) \approx \Phi(\gamma_{c-1} - \mu_{\alpha r}^* - \mu_{\beta r}^*\mu_{\theta p}^*) - \Phi(\gamma_{c-1} - \mu_{\alpha r}^* - \mu_{\beta r}^*\mu_{\theta p}^*),$$

where $\mu_{\alpha r}^*$, $\mu_{\beta r}^*$, and $\mu_{\theta p}^*$ are current estimates of posterior means.

For the prior distributions, it is assumed that each $\alpha_r$ follows $\mathcal{N}(\mu_{\alpha r}, \sigma_{\alpha r}^2)$, each $\beta_r$ follows $\mathcal{N}(\mu_{\beta r}, \sigma_{\beta r}^2)$, and each $\theta_p$ follows $\mathcal{N}(\mu_{\theta p}, \sigma_{\theta p}^2)$ with all parameters mutually independent. As $\gamma$ values are not of primal interest, we suggest to set these values by observed proportions of $\{y^{\text{obs}} = c\}$ rather than treating them as unknown parameters. Priors such as improper uniform and normal may be used; however, they result in more complicated algorithms.

Now define

$$\alpha_r^* = \frac{\alpha_r - \mu_{\alpha r}}{\sigma_{\alpha r}}, \beta_r^* = \frac{\beta_r - \mu_{\beta r}}{\sigma_{\beta r}}, \theta_p^* = \frac{\theta_p - \mu_{\theta p}}{\sigma_{\theta p}}. \quad (6)$$

Denote $\alpha = (\alpha_1, ..., \alpha_R)^T$, $\beta = (\beta_1, ..., \beta_R)^T$, $\theta = (\theta_1, ..., \theta_P)^T$, and similarly for $\alpha^*, \beta^*, \theta^*$. Then, the posterior distribution of $(\alpha^*, \beta^*, \theta^*)$ given data $Y^{\text{obs}}$ is

$$\begin{aligned} & p(\alpha^*, \beta^*, \theta^* | Y^{\text{obs}}) \\ \propto \ & \phi(\alpha^*, \beta^*, \theta^*) \prod_{p,r: z_{pr}=0} \{\Phi(\gamma_{y^o_{pr}} - \alpha_r - \beta_r\theta_p) - \Phi(\gamma_{y^o_{pr}-1} - \alpha_r - \beta_r\theta_p)\}. \end{aligned}$$

In particular, if there is only one new observation $y^o_{pr} = c$, then the corresponding likelihood is

$$L(\alpha_r, \beta_r, \theta_p; y^o_{pr}) = \Phi(\gamma_c - \alpha_r - \beta_r\theta_p) - \Phi(\gamma_{c-1} - \alpha_r - \beta_r\theta_p). \tag{7}$$

Since (7) only involves $(\alpha_r, \beta_r, \theta_p)$, we need only to adjust posterior distribution of the three parameters $\alpha^*_r, \beta^*_r, \theta^*_p$. The posterior density of $(\alpha^*_r, \beta^*_r, \theta^*_p)$ given $y^o_{pr}$ is

$$p(\alpha^*_r, \beta^*_r, \theta^*_p | y^o_{pr}) \propto \phi(\alpha^*_r, \beta^*_r, \theta^*_p) L(\alpha_r, \beta_r, \theta_p), \tag{8}$$

which of the form for a version of Stein's identity. Therefore, we apply it to obtain the posterior means and variances of $\alpha^*_r, \beta^*_r, \theta^*_p$. Then, by (6) we can easily convert these moments to that of $\alpha_r, \beta_r, \theta_p$; for instance,

$$\begin{aligned} E(\alpha_r | y^o_{pr}) &= \mu_{\alpha r} + \sigma_{\alpha r} E(\alpha^*_r | y^o_{pr}) \\ Var(\alpha_r | y^o_{pr}) &= \sigma^2_{\alpha r} Var(\alpha^*_r | y^o_{pr}). \end{aligned} \tag{9}$$

The following functions are needed when taking derivatives of $L$ in (8). Let

$$\begin{aligned} M_a(x) &= \frac{\phi(x) - \phi(x-a)}{\Phi(x) - \Phi(x-a)} \\ N_a(x) &= \frac{x\phi(x) - (x-a)\phi(x-a)}{\Phi(x) - \Phi(x-a)} + \left(\frac{\phi(x) - \phi(x-a)}{\Phi(x) - \Phi(x-a)}\right)^2. \end{aligned} \tag{10}$$

For posterior means, applying a version of Stein's identity gives

$$E(\alpha^*_r | y^o_{pr}) = E\left(\frac{\partial L / \partial \alpha^*_r}{L} \bigg| y^o_{pr}\right) = -\sigma_{\alpha r} E\left(M_a(x) | y^o_{pr}\right), \tag{11}$$

where

$$x = \gamma_c - \alpha_r - \beta_r\theta_p; \qquad a = \gamma_c - \gamma_{c-1} \tag{12}$$

and hence

$$M_a(x) = \frac{\phi(\gamma_c - \alpha_r - \beta_r\theta_p) - \phi(\gamma_{c-1} - \alpha_r - \beta_r\theta_p)}{\Phi(\gamma_c - \alpha_r - \beta_r\theta_p) - \Phi(\gamma_{c-1} - \alpha_r - \beta_r\theta_p)}.$$

Similarly, we have

$$E(\beta_r^*|y_{pr}^o) = E\left(\frac{\partial L/\partial\beta_r^*}{L}\Big|y_{pr}^o\right) = -\sigma_{\beta r}E\left(\theta_p M_a(x)\Big|y_{pr}^o\right) \tag{13}$$

$$E(\theta_p^*|y_{pr}^o) = E\left(\frac{\partial L/\partial\theta_p^*}{L}\Big|y_{pr}^o\right) = -\sigma_{\theta p}E\left(\beta_r M_a(x)\Big|y_{pr}^o\right). \tag{14}$$

The expressions of the posterior variance can be obtained similarly. We have

$$\begin{aligned} Var(\alpha_r^*|y_{pr}^o) =& 1-(\sigma_{\alpha r})^2 E\left[N_a(x)\Big|y_{pr}^o\right], \\ Var(\beta_r^*|y_{pr}^o) =& 1-(\sigma_{\beta r}\theta_p)^2 E\left[N_a(x)\Big|y_{pr}^o\right], \\ Var(\theta_r^*|y_{pr}^o) =& 1-(\sigma_{\theta p}\beta_r)^2 E\left[N_a(x)\Big|y_{pr}^o\right]. \end{aligned}$$

The approximation of expectations are as in Weng and Lin [5], where the error incurred by this approximation is reduced by a scaling factor. Take $E(\alpha_r^*|y_{pr}^o)$ in (11) for illustration:

$$\begin{aligned} E(\alpha_r^*|y_{pr}^o) =& -\sigma_{\alpha r}E\left[M_a(x)\Big|y_{pr}^o\right] \\ \approx& -\frac{\sigma_{\alpha r}}{\nu}M_{a_\nu}(x_\nu), \end{aligned} \tag{15}$$

where $a$ and $x$ are as in (12), $\nu = \sqrt{1+\sigma_{\alpha r}^2+\sigma_{\beta r}^2\mu_{\theta p}^2+\sigma_{\theta p}^2\mu_{\beta r}^2}$, and

$$a_\nu = \frac{\gamma_c-\gamma_{c-1}}{\nu} \qquad \text{and} \qquad x_\nu = \frac{\gamma_c-\mu_{\alpha r}-\mu_{\beta r}\mu_{\theta p}}{\nu}. \tag{16}$$

Together with (9), we have

$$E(\alpha_r|y_{pr}^o) \approx \mu_{\alpha r} - \frac{\sigma_{\alpha r}^2}{\nu}\left[\frac{\phi(\frac{\gamma_c-\mu_{\alpha r}-\mu_{\beta r}\mu_{\theta p}}{\nu})-\phi(\frac{\gamma_{c-1}-\mu_{\alpha r}-\mu_{\beta r}\mu_{\theta p}}{\nu})}{\Phi(\frac{\gamma_c-\mu_{\alpha r}-\mu_{\beta r}\mu_{\theta p}}{\nu})-\Phi(\frac{\gamma_{c-1}-\mu_{\alpha r}-\mu_{\beta r}\mu_{\theta p}}{\nu})}\right]. \tag{17}$$

Similar approximations give

$$Var(\alpha_r|y_{pr}^o) \approx \sigma_{\alpha r}^2\left\{1-\left(\frac{\sigma_{\alpha r}}{\nu}\right)^2 N_{a_\nu}(x_\nu)\right\}. \tag{18}$$

The proposed algorithm is described below:

Step 1. Given current estimates $\mu_\alpha^{(t)}$, $\mu_\beta^{(t)}$, $\mu_\theta^{(t)}$, $\sigma_\alpha^{(t)}$, $\sigma_\beta^{(t)}$, $\sigma_\theta^{(t)}$, where $\mu_\alpha^{(t)} = (\mu_{\alpha 1}^{(t)},\cdots,\mu_{\alpha R}^{(t)})^T$, $\mu_\beta^{(t)} = (\mu_{\beta 1}^{(t)},\cdots,\mu_{\beta R}^{(t)})^T$, $\mu_\theta^{(t)} = (\mu_{\theta 1}^{(t)},\cdots,\mu_{\theta P}^{(t)})^T$, and similarly for $\sigma_\alpha^{(t)}$, $\sigma_\beta^{(t)}$, $\sigma_\theta^{(t)}$.

Step 2. Given the $(t+1)$st observation $y_{pr} = c$. Calculate

$$\nu^{(t)} = \sqrt{1 + (\sigma_{\alpha r}^{(t)})^2 + (\sigma_{\beta r}^{(t)})^2(\mu_{\theta p}^{(t)})^2 + (\sigma_{\theta p}^{(t)})^2(\mu_{\beta r}^{(t)})^2}, \tag{19}$$

$$\omega^{(t)} = -\frac{1}{\nu^{(t)}} M_{a_\nu^{(t)}}(x_\nu^{(t)}), \tag{20}$$

$$\delta^{(t)} = \frac{1}{\left(\nu^{(t)}\right)^2} N_{a_\nu^{(t)}}(x_\nu^{(t)}), \tag{21}$$

where

$$a_\nu^{(t)} = \frac{\gamma_c - \gamma_{c-1}}{\nu^{(t)}} \qquad \text{and} \qquad x_\nu^{(t)} = \frac{\gamma_{c-1} - \mu_{\alpha r}^{(t)} - \mu_{\beta r}^{(t)}\mu_{\theta p}^{(t)}}{\nu^{(t)}}.$$

Step 3. Update parameters as below:

$$\begin{aligned}
\mu_{\alpha r}^{(t+1)} &= \mu_{\alpha r}^{(t)} + \left(\sigma_{\alpha r}^{(t)}\right)^2 \omega^{(t)} \\
\mu_{\beta r}^{(t+1)} &= \mu_{\beta r}^{(t)} + \left(\sigma_{\beta r}^{(t)}\right)^2 \mu_{\theta p}^{(t)}\omega^{(t)} \\
\mu_{\theta p}^{(t+1)} &= \mu_{\theta p}^{(t)} + \left(\sigma_{\theta p}^{(t)}\right)^2 \mu_{\beta r}^{(t)}\omega^{(t)} 
\end{aligned} \tag{22}$$

$$(\sigma_{\alpha r}^{(t+1)})^2 = (\sigma_{\alpha r}^{(t)})^2 \max\left(1 - (\sigma_{\alpha r}^{(t)})^2\delta^{(t)}, \kappa\right) \tag{23}$$

$$(\sigma_{\beta r}^{(t+1)})^2 = (\sigma_{\beta r}^{(t)})^2 \max\left(1 - (\sigma_{\beta r}^{(t)}\mu_{\theta p}^{(t)})^2\delta^{(t)}, \kappa\right) \tag{24}$$

$$(\sigma_{\theta p}^{(t+1)})^2 = (\sigma_{\theta p}^{(t)})^2 \max\left(1 - (\sigma_{\theta r}^{(t)}\mu_{\beta r}^{(t)})^2\delta^{(t)}, \kappa\right). \tag{25}$$

## 4 Experiments

We consider the ratings of news outlets from Mondo Times (`http://www.mondotimes.com/`) used in Ho and Quinn [2]. Mondo Times is an online company that disseminates information about media outlets such as newspapers, magazines, radio stations, and television stations in 211 countries. Raters submit five-point ratings of the content quality of news outlets from awful, poor, average, very good, to great. The dataset used in Ho and Quinn [2], which features 1,515 products (news outlets) and 946 raters, is available from their Ratings package (available at `http://cran.r-project.org/`). The average number of ratings for a product is 3.0 and the average number rated by a rater is 4.8.

As in Ratings of Ho and Quinn [2], we remove raters who rate less than five products and remove products that are only rated by these raters. This ends up with 3249 ratings from 232 raters on 1344 products.

| News outlets | MCMC: sub-Mondo | online: sub-Mondo | online: whole-Mondo |
|---|---|---|---|
| US News & World Report | -0.215 (0.481) | 0.259 (0.241) | -0.148 (0.320) |
| Toronto Sun | -1.027 (0.392) | -0.684 (0.160) | -0.743 (0.224) |
| Toronto Star | 0.397 (0.400) | 0.321 (0.148) | 0.215 (0.199) |
| San Diego Union Tribune | 0.089 (0.482) | 0.124 (0.280) | 0.426 (0.224) |
| People | -1.793 (0.593) | -1.970 (0.689) | -1.909 (0.413) |
| PBS | 1.223 (0.393) | 1.695 (0.258) | 0.809 (0.182) |
| Montana Magazine | -0.233 (0.358) | -0.071 (0.171) | 0.060 (0.199) |
| London Sun | -2.140 (0.569) | -1.477 (0.267) | -1.380 (0.312) |
| Great Falls Tribune | -2.839 (0.770) | -1.817 (0.399) | -2.353 (0.484) |
| Daily Utah Chronicle | 0.054 (0.818) | -0.161 (0.256) | -0.686 (0.668) |
| Colorado Public Radio | 1.431 (0.602) | 2.572 (0.700) | 1.617 (0.484) |
| CNN | 0.038 (0.192) | -0.055 (0.078) | 0.312 (0.074) |

Table 1: Posterior means of $\theta$ for twelve outlets.

As in Ho and Quinn [2], we assume that each $\alpha_r$ follows $\mathcal{N}(1,1)$ and each $\theta_p$ follows $\mathcal{N}(0,1)$. Instead of letting each $\beta_r$ follow $N(-5,20)$ truncated to positive, we assume that each $\beta_r$ follows $\mathcal{N}(1,20)$. All parameters are assumed to be mutually independent. Since the $\gamma$ values are not the main interest here, we set them by the following steps: first, calculate the observed proportions $\#\{y_{pr}=c\}/N$, for $c=1,...,5$, where $N$ is the number of observed ratings; next, find the $z$-scores corresponding to these areas; then, obtain approximations of the mean and variance of $y^*$ and convert the $z$-scores to $y^*$'s scale. In our scenario, the new ratings arrive sequentially. So, the empirical proportions are based on just part of the data, or in a pilot study.

The initial parameter values in Algorithm 1 are set to be $\mu_{\alpha r}^{(0)}=1$, $\mu_{\beta r}^{(0)}=1$, $\mu_{\theta p}^{(0)}=1$, $\sigma_{\alpha r}^{(0)}=1$, $\sigma_{\beta r}^{(0)}=1$, $\sigma_{\theta p}^{(0)}=1$, for $r=1,...,R$ and $p=1,...,P$; and the positive lower bound $\kappa$ in (23)-(25) is set to be 0.0001.

## 5 Conclusions

Ho and Quinn [2] have demonstrated the advantages of fitting the IRT models to Internet ratings data. However, for a real-time data pipeline that continuously collects new ratings on new items, their MCMC approach is not computationally viable. Our proposed online method can adjust the model parameters in a large-scale problem.

## References

[1] J.-P. Fox and C. A. W. Glas. Bayesian estimation of a multilevel IRT model using Gibbs sampling. *Psychometrika*, 66:269–286, 2001.

[2] D. E. Ho and K. M. Quinn. Improving the presentation and interpretation of online ratings data with model-based figures. *The American Statistician*, 62(4):279–288, 2008.

[3] R. J. Patz and B. Junker. A straightforward approach to Markov Chain Monte Carlo methods for item response models. *Journal of Educational and Behavioral Statistics*, 24:146–178, 1999.

[4] X. Wang, J. O. Berger, and D. S. Burdick. Bayesian analysis of dynamic item response models in educational testing. *The Annals of Applied Statistics*, 7(1):126–153, 2013.

[5] R. C. Weng and C.-J. Lin. A Bayesian approximation method for online ranking. *Journal of Machine Learning Research*, 12:267–300, 2011.

**Report on attending The 59th World Statistics Congress (WSC) Aug. 25 - 30, 2013, Hong Kong**

The International Statistical Institute (ISI), established in 1885, is one of the oldest scientific associations. It dedicates to promote the statistics profession. The ISI is best renowned for its biennial World Statistics Congress (WSC), where the international statistical community congregates to exchange ideas, develop new links and discuss current trends and developments in the statistical world. This year WSC was held in Hong Kong during 25-30 August 2013. The meeting venue was the Hong Kong Convention and Exhibition Centre (HKCEC). It covers a wide range of topics and features the latest scientific developments in the fields of probability and statistics and their applications.

This year I presented the paper "An analysis of online ratings data" in a poster spotlight session, scheduled on Tuesday (August 27th) morning. I got a good chance to present my work and communicate with many people about my research. I also attended several oral presentations, and was impressed by some talks such as talks in a History session on "Jacob Bernoulli's *Ars Conjectandi* and the emergence of probability" sponsored by Bernoulli Society to celebrate the 300 anniversary of the publication of this paper, talks about latent variable modeling in the session "Latent variable modeling of complex survey data," a talk about "Business analytics and big data: what do statisticians need to succeed?" by Robert N. Rodriguez in the session "Special invited panel on career development," especially designed for the Youth Theme. I also visited academic book booths in the Exhibition Hall and the Career Placement Service to learn more about information about current statistical job market.

During these days, I met some people from both industry and university. Having chats with them inspired me and encouraged me to keep on moving. It was a fruitful trip.

# 國科會補助計畫衍生研發成果推廣資料表

日期:2013/09/18

| | |
|---|---|
| 國科會補助計畫 | 計畫名稱: 貝氏方法在網路評分資料之應用 |
| | 計畫主持人: 翁久幸 |
| | 計畫編號: 100-2118-M-004-001-MY2　　學門領域: 貝氏統計 |

無研發成果推廣資料

# 100 年度專題研究計畫研究成果彙整表

| 計畫主持人：翁久幸 | 計畫編號：100-2118-M-004-001-MY2 |
|---|---|
| 計畫名稱：貝氏方法在網路評分資料之應用 | |

| 成果項目 | | | 量化：實際已達成數（被接受或已發表） | 量化：預期總達成數(含實際已達成數) | 量化：本計畫實際貢獻百分比 | 單位 | 備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等） |
|---|---|---|---|---|---|---|---|
| 國內 | 論文著作 | 期刊論文 | 0 | 0 | 100% | 篇 | |
| | | 研究報告/技術報告 | 0 | 0 | 100% | | |
| | | 研討會論文 | 0 | 0 | 100% | | |
| | | 專書 | 0 | 0 | 100% | | |
| | 專利 | 申請中件數 | 0 | 0 | 100% | 件 | |
| | | 已獲得件數 | 0 | 0 | 100% | | |
| | 技術移轉 | 件數 | 0 | 0 | 100% | 件 | |
| | | 權利金 | 0 | 0 | 100% | 千元 | |
| | 參與計畫人力（本國籍） | 碩士生 | 0 | 2 | 100% | 人次 | |
| | | 博士生 | 0 | 1 | 100% | | |
| | | 博士後研究員 | 0 | 0 | 100% | | |
| | | 專任助理 | 0 | 0 | 100% | | |
| 國外 | 論文著作 | 期刊論文 | 0 | 1 | 100% | 篇 | |
| | | 研究報告/技術報告 | 0 | 1 | 100% | | |
| | | 研討會論文 | 0 | 1 | 100% | | |
| | | 專書 | 0 | 0 | 100% | 章/本 | |
| | 專利 | 申請中件數 | 0 | 0 | 100% | 件 | |
| | | 已獲得件數 | 0 | 0 | 100% | | |
| | 技術移轉 | 件數 | 0 | 0 | 100% | 件 | |
| | | 權利金 | 0 | 0 | 100% | 千元 | |
| | 參與計畫人力（外國籍） | 碩士生 | 0 | 0 | 100% | 人次 | |
| | | 博士生 | 0 | 0 | 100% | | |
| | | 博士後研究員 | 0 | 0 | 100% | | |
| | | 專任助理 | 0 | 0 | 100% | | |

| | |
|---|---|
| 其他成果<br>(無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。) | 無 |

| | 成果項目 | 量化 | 名稱或內容性質簡述 |
|---|---|---|---|
| 科教處計畫加填項目 | 測驗工具(含質性與量性) | 0 | |
| | 課程/模組 | 0 | |
| | 電腦及網路系統或工具 | 0 | |
| | 教材 | 0 | |
| | 舉辦之活動/競賽 | 0 | |
| | 研討會/工作坊 | 0 | |
| | 電子報、網站 | 0 | |
| | 計畫成果推廣之參與（閱聽）人數 | 0 | |

# 國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

   ■達成目標

   □未達成目標（請說明，以 100 字為限）

   　　□實驗失敗

   　　□因故實驗中斷

   　　□其他原因

   說明：

2. 研究成果在學術期刊發表或申請專利等情形：

   論文：□已發表 □未發表之文稿 ■撰寫中 □無

   專利：□已獲得 □申請中 ■無

   技轉：□已技轉 □洽談中 ■無

   其他：（以 100 字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）

   此研究之即時方法可應用於實際問題.