MODULE HANDBOOK

# BAYESSIAN ANALYSIS

BACHELOR DEGREE PROGRAM
DEPARTEMENT OF STATISTICS
FACULTY OF SCIENCE AND DATA ANALYTICS
INSTITUT TEKNOLOGI SEPULUH NOPEMBER

**ENDORSEMENT**

# MODULE HANDBOOK
## BAYESSIAN ANALYSIS
## DEPARTMENT OF STATISTICS
**INSTITUT TEKNOLOGI SEPULUH NOPEMBER**

| **Proses** ***Process*** | **Penanggung Jawab** ***Person in Charge*** | | | **Tanggal** ***Date*** |
|---|---|---|---|---|
| | **Nama** ***Name*** | **Jabatan** ***Position*** | **Tandatangan** ***Signature*** | |
| Perumus *Preparation* | Dr. Santi Wulan Purnami, M.Si | Dosen *Lecturer* | | **March 28, 2019** |
| Pemeriksa dan Pengendalian *Review and Control* | Dr. Santi Wulan Purnami, M.Si | Tim kurikulum *Curriculum team* | | **April 15, 2019** |
| Persetujuan *Approval* | Dr. Santi Wulan Purnami, M.Si | Koordinator RMK *Course Cluster Coordinator* | | **July 17, 2019** |
| Penetapan *Determination* | Dr. Kartika Fithriasari, M.Si | Kepala Departemen *Head of Department* | | **July 30, 2019** |

# MODULE HANDBOOK
# BAYESSIAN ANALYSIS

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| Module name | BAYESSIAN ANALYSIS | |
| Module level | Undergraduate | |
| Code | KS184626 | |
| Course (if applicable) | BAYESSIAN ANALYSIS | |
| Semester | Sixth Semester | |
| Person responsible for the module | Dr. Santi Wulan Purnami, M.Si | |
| Lecturer | Dr. Santi Wulan Purnami, M.Si | |
| Language | Bahasa Indonesia and English | |
| Relation to curriculum | Undergradute degree program,**optional**, 6$^{th}$ semester. | |
| Type of teaching, contact hours | Lectures, <50 students | |
| Workload | 1. Lectures : 3 x 50 = 100 minutes per week.<br>2. Exercises and Assignments : 3 x 60 = 180 minutes (3 hours) per week.<br>3. Private learning : 3 x 60 = 130 minutes (3 hours) per week. | |
| Credit points | 3 credit points (sks) | |
| Requirements according to the examination regulations | A student must have attended at least 80% of the lectures to sit in the exams. | |
| Mandatory prerequisites | Regression Analysis | |
| Learning outcomes<br><br>and their<br><br>corresponding PLOs | *CLO. 1 Able to identify data distribution with the goodness of fit test and be able to estimate data distribution parameters frequently in*<br>*CLO. 2 Able to distinguish and pattern Value of parameter estimation if given data from observations in differ*<br>*rent situations and conditions.*<br>*CLO. 3 Be able to explain and differentiate ways of determining the types of priors and hyper-prior structures required in theparameter estimation process.*<br>*CLO. 4 Able to determine the prior distribution of discrete distribution parametersand continuous which has one parameter (Discrete: Bernoulli, Poisson; Continuous: Experimental, Normal-sigma known)*<br>. | PLO-01<br><br>PLO-03 |

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| | *CLO. 5 Be able to determine the posterior distribution of discrete and continuous distribution parameters which have one parameter*<br>*CLO. 6 Be able to explain the basic principles of Bayesian computation in constructing the posterior distribution of parameters from a numerically parameter data pattern*<br>*CLO. 7 Able to compile a posterior data generator algorithm with a single parameter distribution parameter*<br>*CLO. 8 Able to explain the Markov Cain Monte Carlo concept in theparameter estimation.*<br>*CLO. 9 Able to create and explain doodle structure and posterior estimation program syntax in WinBUGS for a distribution model with a single parameter*<br>*CLO. 10 Able to use WinBUGS to estimate and test parameter hypotheses from distributed data with a single parameter*<br>*CLO. 11 Able to determine the prior distribution of discrete and continuous distribution parameters that have more than one parameter (Discrete: Binomial; Continuous: Normal, Gamma, Weibull).*<br>*CLO. 12 Able to mene Determine the posterior distribution of discrete and continuous distribution parameters that have more than oneparameter.*<br>*CLO. 13 Be able to determine the prior and posterior parameters in a simple linear regression model to estimate a Bayesian linear regression model using WinBUGS*<br>*CLO. 14 Be able to explain and apply the Bayes principle of factors for model selection best*<br>*CLO. 15 Able to communicate effectively and cooperate in interdisciplinary and multidisciplinary teams*<br>*CLO. 16 Have responsibility and professional ethics*<br>*CLO. 17 Able to motivate oneself to think creatively and learn lifelong* | PLO-04<br><br>PLO-05 |
| Content | *This course discusses the concept and application of the Bayesian method to perform data driven statistical inference which includes estimating distribution parameters and estimating statistical models, as well as selecting the best model for a data. The learning process starts from discussing the concept of Bayes' theorem, introducing and determining the prior distribution, and arranging the posterior distribution. The estimation of the posterior model is done both mathematically and computationally by applying Bayesian MCMC in WinBUGS. The implementation of Bayesian analysis will be carried out for both single and multiple parameterized models and for simple linear regression. It also discusses the comparisons (advantages and disadvantages) of the Bayesian and frequentist methods. At the end of the lecture, it will be discussed how to choose the best model in Bayesian* | |

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| | *modeling.* |
| Study and examination requirements and forms of examination | • In-class exercises<br>• Assignment 1, 2, 3<br>• Mid-term examination<br>• Final examination |
| Media employed | LCD, whiteboard, websites (myITS Classroom), zoom. |
| Reading list | 1. Albert, J., 2009. *Bayesian Computation With R*. 2nd edition. New York, USA : Springer.<br>2. Gelman, A., Carlin, J. B., Stern, H. S. Dunson, D.B., Vehtari, A. and Rubin, D. B., 2014. *Bayesian Data Analysis*. London: Chapman dan Hall.<br>3. Ghosh, J.K., Delampady, M., and Samanta, T., 2006. *An Introduction to Bayesian Analisis: Theory and Methods*. New York, USA : Springer.<br>4. Kruschke, J.K., 2010. *Doing Bayesian Data Analysis: A Tutorial with R and BUGS*. Academic Press.<br>5. Ntzoufras, I., 2009. *Bayesian Modeling Using WinBUGS*. New Jersey, USA : John Wiley dan Sons.<br>6. Robert, C. P., 2007. *The Bayesian Choice: From Decision-Theoretic Foundations to Computational Implementation*. 2nd edition. New York, USA : Springer.<br>7. Tanner, M. A., 1996. *Tools for Statistical Inference: Methods for the Exploration of Posterior Distributions and Likelihood Functions*. 3rd edition. New York : Springer-Verlag.. |

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| | Program Studi | Sarjana, Departemen Statistika, FMKSD-ITS |
| | Mata Kuliah | Analisis Bayesian |
| | Kode Mata Kuliah | KS184626 |
| | Semester/SKS | VI/3 |
| | MK Prasyarat | Analisis Regresi |
| **RP-S1** | Dosen Pengampu | |

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| **Bahan Kajian**<br>*Study Materials* | Dasar Sains, Teori Statistika, Deskripsi dan Eksplorasi, Komputasi dan Data Processing, Pemodelan, Industri dan Bisnis, Pemerintahan dan Kependudukan, Ekonomi dan Manajemen, Kesehatan dan Lingkungan, Sosial Humaniora<br>*Basic of Science, Statistical Theory, Description and Exploration, Computing and Data Processing, Modeling, Industry and Business, Government and Population, Economics and Management, Health and Environment, Social Humanities* |
| **CPL yang dibebankan MK**<br>*PLO* | CPL-1 Mampu menerapkan pengetahuan teori statistika, matematika, dan komputasi<br>CPL-3 Mampu menganalisis data dengan metode statistika yang tepat dan mengintepretasikannya<br>CPL-4 Mampu mengindentifikasi,memformulasi, dan menyelesaikan masalah statistika di berbagai bidang terapan<br>CPL-5 Mampu menggunakan teknik komputasi dan perangkat komputer modern yang diperlukan dalam bidang statistika dan sains data<br><br>*PLO-1 Able to apply knowledge of statistical theory, mathematics, and computation*<br>*PLO-3 Able to analyze data with appropriate statistical methods and interpret it*<br>*PLO-4 Able to identify, formulate, and solve statistical problems in variousapplied fields*<br>*PLO-5 Able to use computational techniques and modern computer equipment required in the field of statistics and data science* |
| **CP-MK**<br>*CLO* | CPMK.1 Mampu mengidentifikasi distribusi data dengan uji goodness of fit dan mampu melakukan estimasi parameter distribusi data secara frequentis<br>CPMK.2 Mampu membedakan dan mempolakan nilai estimasi parameter jika diberikan data dari pengamatan pada situasi dan kondisi yang berbeda-beda<br>CPMK.3 Mampu menjelaskan dan membedakan cara penentuan jenis-jenis prior dan struktur hiper-prior yang dibutuhkan dalam proses estimasi parameter<br>CPMK.4 Mampu menentukan distribusi prior parameter distribusi diskrit dan kontinyu yang mempunyai satu parameter (Diskrit: Bernoulli, Poisson; Kontinyu: Eksponsnsial, Normal-sigma diketahui)<br>CPMK.5 Mampu menentukan distribusi posterior parameter distribusi diskrit dan kontinyu yang mempunyai satu parameter<br>CPMK.6 Mampu menjelaskan prinsip dasar komputasi Bayesian dalam membangun distribusi posterior parameter dari pola data berparameter 6tunggal secara numerik<br>CPMK.7 Mampu menyusun algoritma pembangkit data posterior parameter distribusi yang berparameter tunggal<br>CPMK.8 Mampu menjelaskan konsep Markov Cain Monte Carlo dalam estimasi parameter<br>CPMK.9 Mampu membuat dan menjelaskan struktur doodle dan sintaks program estimasi posterior dalam WinBUGS untuk model distribusi dengan parameter tunggal |

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| | Semester/SKS | VI/3 |
| | MK Prasyarat | Analisis Regresi |
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| | CPMK.10 Mampu menggunakan WinBUGS untuk melakukan estimasi dan uji hipotesis parameter dari data yang berdistribusi dengan parameter tunggal<br>CPMK.11 Mampu menentukan distribusi prior parameter distribusi diskrit dan kontinyu yang mempunyai lebih dari satu parameter (Diskrit: Binomial; Kontinyu: Normal, Gamma, Weibull)<br>CPMK.12 Mampu menentukan distribusi posterior parameter distribusi diskrit dan kontinyu yang mempunyai lebih dari satu parameter<br>CPMK.13 Mampu menentukan prior dan posterior parameter dalam model regresi linear sederhana untuk mengestimasi model regresi linear secara Bayesian menggunakan WinBUGS<br>CPMK.14 Mampu menjelaskan dan menerapkan prinsip Bayes faktor untuk pemilihan model terbaik<br>CPMK.15 Mampu berkomunikasi secara efektif dan bekerjasama dalam tim yang interdisiplin dan multidisiplin<br>CPMK.16 Memiliki tanggung jawab dan etika profesi<br>CPMK.17 Mampu memotivasi diri untuk berpikir kreatif dan belajar sepanjang hayat<br>*CLO. 1 Able to identify data distribution with the goodness of fit test and be able to estimate data distribution parameters frequently in*<br>*CLO. 2 Able to distinguish and pattern Value of parameter estimation if given data from observations in differ rent situations and conditions.*<br>*CLO. 3 Be able to explain and differentiate ways of determining the types of priors and hyper-prior structures required in theparameter estimation process.*<br>*CLO. 4 Able to determine the prior distribution of discrete distribution parametersand continuous which has one parameter (Di screte: Bernoulli, Poisson; Continuous: Experimental, Normal-sigma known)*<br>*CLO. 5 Be able to determine the posterior distribution of discrete and continuous distribution parameters which have one para meter of*<br>*CLO. 6 Be able to explain the basic principles of Bayesian computation in constructing the posterior distribution of parameters from a numerically parameter data pattern*<br>*CLO. 7 Able to compile a posterior data generator algorithm with a single parameter distribution parameter*<br>*CLO. 8 Able to explain the Markov Cain Monte Carlo concept in theparameter estimation.*<br>*CLO. 9 Able to create and explain doodle structure and posterior estimation program syntax in WinBUGS for a distribution mode l with a single parameter*<br>*CLO. 10 Able to use WinBUGS to estimate and test parameter hypotheses from distributed data with a single parameter*<br>*CLO. 11 Able to determine the prior distribution of discrete and continuous distribution parameters that have more than one p arameter (Discrete: Binomial; Continuous: Normal, Gamma, Weibull).*<br>*CLO. 12 Able to mene Determine the posterior distribution of discrete and continuous distribution parameters that have more than oneparameter.* |

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| | *CLO. 13 Be able to determine the prior and posterior parameters in a simple linear regression model to estimate a Bayesian linear regression model using WinBUGS*<br>*CLO. 14 Be able to explain and apply the Bayes principle of factors for model selection best*<br>*CLO. 15 Able to communicate effectively and cooperate in interdisciplinary and multidisciplinary teams*<br>*CLO. 16 Have responsibility and professional ethics*<br>*CLO. 17 Able to motivate oneself to think creatively and learn lifelong* |

| **Perte-muan** *Meeting* | **Kemampuan Akhir Sub CP-MK** *Final Ability* | **Keluasan (materi pembelajaran)** *Extent (learning material)* | **Metode Pembelajaran** *Learning methods* | **Estimasi Waktu** *Duration* | **Bentuk Evaluasi** *Evaluation Type* | **Kriteria dan Indikator Penilaian** *Assessment Criteria and Indicators* | **Bobot Penilaian** *Scoring* |
|---|---|---|---|---|---|---|---|
| 1 | Mampu membedakan konsep Bayesian dan non-Bayesian (frequentist) | Teorema Bayes dan Bayesian inference | CIDLSP | 100 menit | - Tugas<br>- Observasi di kelas | 1. Memahami konsep hukum Bayes<br>2. Memahami perbedaan cara berfikir Bayesian vs frequentist | 05%/05% |
| *1* | *Be able to distinguish between Bayesian and non-Bayesian concepts (frequentist)* | *Bayesian theorem and Bayesian inference* | *CIDLSP* | *100 minutes* | *- task*<br>*- Observationin class* | *1. Understand the concept of Bayes law*<br>*3. Understand the difference in Bayesian vs frequency thinking entist* | *05% / 05%* |
| 2 | Mampu mengidentifikasi distribusi data dengan uji *goodness of fit* dan mampu melakukan estimasi parameter distribusi data secara frequentis | MLE, Kolmogorov-Smirnov | CIDLSP | 50 menit | - Tugas<br>- Observasi di kelas<br>- Tes<br>Presentasi dan makalah | Memahami cara identifikasi dan karakteristik distribusi data | 07%/12% |
| *2* | *Able to identify data distribution withtest goodness of fit and able* | *MLE, Kolmogorov-Smirnov* | *CIDLSP* | *50 minutes* | *- task*<br>*- Observationin class* | *Understand how to identify and characteristics of data distribution* | *07% / 12%* |

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| **Perte-muan** *Meeting* | **Kemampuan Akhir Sub CP-MK** *Final Ability* | **Keluasan (materi pembelajaran)** *Extent (learning material)* | **Metode Pembelajaran** *Learning methods* | **Estimasi Waktu** *Duration* | **Bentuk Evaluasi** *Evaluation Type* | **Kriteria dan Indikator Penilaian** *Assessment Criteria and Indicators* | **Bobot Penilaian** *Scoring* |
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| | *to estimate data distribution parameters frequentlyis* | | | | - *test*<br>- *Presentationand paper* | | |
| 3 | Mampu membedakan dan mempolakan nilai estimasi parameter jika diberikan data dari pengamatan pada situasi dan kondisi yang berbeda-beda | Parameter model sebagai variabel | CIDLSP | 150 menit | - Tugas<br>- Observasi di kelas<br>- Tes<br>Presentasi dan makalah | Memahami parameter distribusi data selalu mempunyai pola tertentu | 10%/22% |
| *3* | *Able to distinguish and pattern the estimated parameter values if given data from observations in different situations and conditions* | *Model parameters asvariables* | *CIDLSP* | *150 minutes* | - *task*<br>- *Observationin class*<br>- *tests*<br>- *Presentationand papers* | *Understanding data distribution parameters always have a certain pattern* | *10% / 22%* |
| 4 | Mampu menjelaskan dan membedakan cara penentuan jenis-jenis prior dan struktur hiper-prior yang dibutuhkan dalam proses estimasi parameter | Jenis Prior dan hiper-prior | CIDLSP | 100 menit | - Tugas<br>- Observasi di kelas<br>- Tes<br>Presentasi dan makalah | 1. Memahami jenis prior conjugate/nonconjugate; informative/noninformative; proper/improper; dan pseudo-prior dan kombinasinya<br>2. Memahami perlu diadakannya hiperprior dalam model Bayesian | 18%/40% |
| *4* | *Able to explain and differentiate the method of determining* | *Prior and hyper-prior* | *CIDLSPtypes* | *100 minutes* | - *task*<br>- *Observationin class* | *1. Understanding conjugate / nonconjugate prior types; informative / noninformative;* | *18% / 40%* |

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| **Perte-muan** *Meeting* | **Kemampuan Akhir Sub CP-MK** *Final Ability* | **Keluasan (materi pembelajaran)** *Extent (learning material)* | **Metode Pembelajaran** *Learning methods* | **Estimasi Waktu** *Duration* | **Bentuk Evaluasi** *Evaluation Type* | **Kriteria dan Indikator Penilaian** *Assessment Criteria and Indicators* | **Bobot Penilaian** *Scoring* |
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| | *the types of priors and hyper-prior structures needed in the process of estimating parameters.* | | | | *- tests*<br>*- Presentationand papers* | *proper / improper; and pseudo-priors and their combinations*<br>*3. Understand the need for hyperpriority in the Bayesianmodel* | |
| 5 | Mampu menentukan distribusi prior parameter distribusi diskrit dan kontinyu yang mempunyai satu parameter (Diskrit: Bernoulli, Poisson; Kontinyu: Eksponsnsial, Normal-sigma diketahui) | Prior Jeffrey's | CIDLSP | 250 menit | - Tugas<br>- Observasi di kelas<br>- Tes<br>Presentasi dan makalah | 1. Mampu memilih prior yang tepat untuk estimasi parameter distribusi Bernoulli dan Poisson secara Bayesian<br>2. Mampu memilih prior yang tepat untuk estimasi parameter distribusi Eksponsnsial, Normal-sigma diketahui secara Bayesian | |
| *5* | *Be able to determine prior distribution of discrete and continuous distribution parameters that have one parameter (Discrete: Bernoulli, Poisson; Continuous: Experimental, Normal-sigma known)* | *Jeffrey's Prior* | *CIDLSP* | *250 minutes* | *- task*<br>*- Observationin class*<br>*- test*<br>*- Presentationand paper* | *1. Able to choose the right priors for estimating Bernoulli and Poisson distribution parameters in Bayesian*<br>*3. Able to choose the right priors for estimating parameters of the Exclusive, Normal-sigma distribution known by Bayesian* | |
| 6 | Mampu menentukan distribusi posterior parameter distribusi | posterior proporsional | CIDLSP | 150 menit | - Tugas<br>- Observasi di kelas | Mampu menghitung probabilitas posterior parameter data yang berdistribusi diskrit (Bernoulli, Poisson) | |

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| **Perte-muan** *Meeting* | **Kemampuan Akhir Sub CP-MK** *Final Ability* | **Keluasan (materi pembelajaran)** *Extent (learning material)* | **Metode Pembelajaran** *Learning methods* | **Estimasi Waktu** *Duration* | **Bentuk Evaluasi** *Evaluation Type* | **Kriteria dan Indikator Penilaian** *Assessment Criteria and Indicators* | **Bobot Penilaian** *Scoring* |
|---|---|---|---|---|---|---|---|
| | diskrit dan kontinyu yang mempunyai satu parameter | | | | - Tes Presentasi dan makalah | dan kontinyu (Eksponsnsial, Normal-sigma diketahui) | |
| *6* | *Able to determine the posterior distribution of discrete distribution parameters and continuous which has one* | *posterior proportional* | *CIDLSPparameter* | *150 minutes* | *- task*<br>*- Observationin class*<br>*- tests*<br>*- Presentation and paper* | *Able to calculate posterior probability of data parameters that have discrete distribution (Bernoulli, Poisson) and continuous (exclusive, normal-sigma known)* | |
| 7 | Mampu menjelaskan prinsip dasar komputasi Bayesian dalam membangun distribusi posterior parameter dari pola data berparameter tunggal secara numerik | Konsep integral dan estimasi parameter komputasional | CIDLSP | 150 menit | - Tugas<br>- Observasi di kelas<br>- Tes Presentasi dan makalah | Mampu menghitung probabilitas posterior parameter data yang berdistribusi diskrit (Bernoulli, Poisson) dan kontinyu (Eksponsnsial, Normal-sigma diketahui) secara algoritmis komputasional | 10%/50% |
| *7* | *Be able to explain the basic principles of computation Bayesian in constructing a posterior distribution of parameters from a single parameter data pattern numerically* | *integral concept and computational parameter estimation* | *CIDLSP* | *150 minutes* | *- task*<br>*- Observationin class*<br>*- test*<br>*- Presentationand paper* | *Able to calculate posterior probability of data parameters that have discrete distribution (Bernoulli, Poisson) and continuous (Experimental, Normal - sigma known) algorithmically computational* | *10% / 50%* |
| **8** | **ETS** | | | | | | |

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| **Perte-muan** *Meeting* | **Kemampuan Akhir Sub CP-MK** *Final Ability* | **Keluasan (materi pembelajaran)** *Extent (learning material)* | **Metode Pembelajaran** *Learning methods* | **Estimasi Waktu** *Duration* | **Bentuk Evaluasi** *Evaluation Type* | **Kriteria dan Indikator Penilaian** *Assessment Criteria and Indicators* | **Bobot Penilaian** *Scoring* |
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| 9 | Mampu menjelaskan konsep Markov Cain Monte Carlo dalam estimasi parameter | Data augmentation dan Markov Chain Monte Carlo (MCMC) | CIDLSP | 50 menit | - Tugas<br>- Observasi di kelas<br>- Tes<br>Presentasi dan makalah | Mampu mengimplementasikan model Bayesian dengan MCMC, khususnya Gibbs sampler dan Metropolis Hasting | 05%/55% |
| *9* | *Able to explain the concept of Markov Cain Monte Carlo in parameter estimation* | *Data augmentation and Markov Chain Monte Carlo (MCMC)* | *CIDLSP* | *50 minutes* | *- task*<br>*- Observationin class*<br>*- test*<br>*- Presentationand paper* | *Able to implement Bayesian model with MCMC, especially Gibbs sampler and Metropolis Hasting* | *05% / 55%* |
| 10 | Mampu membuat dan menjelaskan struktur doodle dan sintaks program estimasi posterior dalam WinBUGS sebagi proses MCMC untuk estimasi model distribusi dengan parameter tunggal | Node (Stokastik, logical, konstan), path, dan Frame sebagai bentuk integralistik estimasi Bayesian | CIDLSP | 150 menit | - Tugas Syntaks WinBUGS<br>- Observasi di kelas<br>- Tes<br>Presentasi dan makalah | Mampu menggunakan WinBUGS untuk penyederhanaan pemodelan Bayesian dengan MCMC | 10%/65% |
| *10* | *Able to create and explain doodle structure and posterior estimation program syntax in WinBUGS as an MCMC process for* | *Node (Stochastic, logical, constant), path, and Frame as an integralistic form of esti Bayesian* | *CIDLSP* | *150 minutes* | *- WinBUGS Syntaks Task*<br>*- Observation inclass*<br>*- Test* | *Able to use WinBUGS for simplification of Bayesian modeling with MCMC* | *10% / 65%* |

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|---|---|---|---|---|---|---|---|
| | *estimating distribution model with single parameter* | | | | - *Presentationand paper* | | |
| 11 | Mampu menggunakan WinBUGS untuk melakukan estimasi dan uji hipotesis parameter dari data yang berdistribusi dengan parameter tunggal | Konvergensi Komputasi Bayes dan uji hipotesis dalam WinBUGS | CIDLSP | 150 menit | - Tugas<br>- Observasi di kelas<br>- Tes<br>Presentasi dan makalah | Mampu membedakan dan memodelkan permasalahan dengan Bayesian single parameter | 05%/70% |
| *11* | *Able to use WinBUGS to estimate and test hypothesis parameters from distributed data with single parameter* | *Bayes Computing Convergence and hypothesis testing in WinBUGS* | *CIDLSP* | *150 minutes* | - *task*<br>- *Observationin class*<br>- *tests*<br>- *Presentationand papers* | *Able to distinguish and model problems with a single Bayesian parameter* | *05% / 70%* |
| 12 | Mampu menentukan distribusi prior parameter distribusi diskrit dan kontinyu yang mempunyai lebih dari satu parameter (Diskrit: Binomial; Kontinyu: Normal, Gamma, Weibull) | Joint prior, independent prior, joint posterior, full conditional posterior | CIDLSP | 250 menit | - Tugas<br>- Observasi di kelas<br>Presentasi dan makalah | Mampu membedakan efek perbedaan prior dalam memodelkan permasalahan dengan Bayesian multiple parameter | 10%/80% |

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| | MK Prasyarat | Analisis Regresi |
| **RP-S1** | Dosen Pengampu | |

| **Perte-muan** *Meeting* | **Kemampuan Akhir Sub CP-MK** *Final Ability* | **Keluasan (materi pembelajaran)** *Extent (learning material)* | **Metode Pembelajaran** *Learning methods* | **Estimasi Waktu** *Duration* | **Bentuk Evaluasi** *Evaluation Type* | **Kriteria dan Indikator Penilaian** *Assessment Criteria and Indicators* | **Bobot Penilaian** *Scoring* |
|---|---|---|---|---|---|---|---|
| *12* | *Able to determine prior distribution of discrete and continuous distribution parameters that have more than one parameter (Discrete: Binomial ; Continuous: Normal, Gamma, Weibull)* | *Joint prior, independent prior, joint posterior, full conditional posterior* | *CIDLSP* | *250 minutes* | *- task<br>- Observationin class<br>- Presentations and papers* | *Able to distinguish the effects of prior differences in modeling problems with Bayesian multiple parameters* | *10% / 80%* |
| 13 | Mampu menentukan distribusi posterior parameter distribusi diskrit dan kontinyu yang mempunyai lebih dari satu parameter | MCMC dan konvergensi Bayesian multiple parameter | CIDLSP | 150 menit | - Tugas WinBUGS<br>- Observasi di kelas<br>Presentasi dan makalah | Mampu membedakan dan memodelkan permasalahan dengan Bayesian multiple parameter | 05%/85% |
| *13* | *Able to determine posterior distribution of discrete and continuous distribution parameters that have more than oneparameter* | *MCMCand Bayesian convergence of multiple parameters* | *CIDLSP* | *150 minutes* | *- WinBUGS task<br>- Observations inclass<br>- presentation and paper* | *Able to distinguish and model problems with Bayesian multiple parameters* | *05% / 85%* |
| 14 | Mampu menentukan prior dan posterior parameter dalam model regresi linear sederhana untuk mengestimasi model regresi linear | Hiper-parameter dan model hirarki | CIDLSP | 150 menit | - Tugas<br>- Observasi di kelas | 1. Mampu memilih dan menyusun prior dan hiper-prior dalam Bayesian regresi<br>2. Mampu menyusun model posterior Bayesian Regresi | 05%/90% |

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|---|---|---|
| | Program Studi | Sarjana, Departemen Statistika, FMKSD-ITS |
| | Mata Kuliah | Analisis Bayesian |
| | Kode Mata Kuliah | KS184626 |
| | Semester/SKS | VI/3 |
| | MK Prasyarat | Analisis Regresi |
| **RP-S1** | Dosen Pengampu | |

| **Perte-muan** *Meeting* | **Kemampuan Akhir Sub CP-MK** *Final Ability* | **Keluasan (materi pembelajaran)** *Extent (learning material)* | **Metode Pembelajaran** *Learning methods* | **Estimasi Waktu** *Duration* | **Bentuk Evaluasi** *Evaluation Type* | **Kriteria dan Indikator Penilaian** *Assessment Criteria and Indicators* | **Bobot Penilaian** *Scoring* |
|---|---|---|---|---|---|---|---|
| | secara Bayesian menggunakan WinBUGS | | | | | | |
| *14* | *Able to determine priors and posterior parameters in a simple linear regression model to estimate a Bayesian linear regression model using WinBUGS* | *Hyper-parameter andhierarchical model* | *CIDLSP* | *150 minutes* | *- task*<br>*- Observationin class*<br>- | *1. Able to select and compile priors and hyper-priors in Bayesian regression*<br>*3. Able to compile a Bayesian posterior model Regression* | *05% / 90 %* |
| 15 | Mampu menjelaskan dan menerapkan prinsip Bayes faktor untuk pemilihan model terbaik | Bayes odds, Struktur Perkalian Distribusi, Deviance | CIDLSP | 250 menit | - Tugas<br>- Observasi di kelas<br>- Tes Presentasi dan makalah | 1. Mampu menyusun model struktur perkalian distribusi<br>2. Mampu menerapkan Bayes faktor dalam pemilihan model | 10%/100% |
| *15* | *Be able to become explain and apply the Bayes factor principle for selecting the best model* | *Bayes odds, Multiplication Distribution Structure, Deviance* | *CIDLSP* | *250 minutes* | *- task*<br>*- Observationin class*<br>*- test*<br>*- Presentationand paper* | *1. Able to build multiplication distribution structure model*<br>*2. Able to apply Bayes factor in model selection* | *10% / 100%* |
| 16 | **EAS** | | | | | | |

**PUSTAKA/***REFERENCES* **:**


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|---|---|---|
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| | Semester/SKS | VI/3 |
| | MK Prasyarat | Analisis Regresi |
| **RP-S1** | Dosen Pengampu | |


2. Kruschke, J.K. (2010) Doing Bayesian Data Analysis: A Tutorial with R and BUGS, Academic Press
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