CONCENTRATION COURSE

CS146: Modern Computational Statistics

TERM
Fall 2017

CREDIT
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Course Description

How do weather scientists know for sure that a hurricane will hit the coast in two days? How would one devise methods to forecast sales of a product? At the end of this course you should be equipped with tools with which to gather and interpret data, but you should also be able to inform a scientific or business decision on the basis of statistically rigorous arguments.

This course covers the theory that underlies computationally intensive statistical methods that are used to solve real-world statistical problems. Topics include exact inference in parametric models, probabilistic graphical models, and approximate inference using Monte Carlo and variational Bayesian methods.

Course Objectives & Learning Outcomes

Develop familiarity through practice of how to set up and manipulate probabilistic models for inference and prediction

#graphicalmodels : Write down a graphical model representation of a joint probability distribution representing a statistical model (or vice versa) and manipulate the graphical notation for simplification, inference and prediction in the model.

#probabilitytheory : When provided with statements of probability, derive related statements of probability – involving marginal, conditional or joint distributions – using the sum rule, product rule and Bayes' rule.

#rightdistribution : Given a data set or real-world situation, use standard properties of probability distributions to select appropriate distributions in one or more variables to represent the scenario.

Learn about various methods for exact and approximate computational inference in complex statistical models

#Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

#analyticalapproximation : Given a statistical model, select appropriate analytical approximations and derive rules with closed form solutions for inference and prediction.

#exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

#montecarlo : Given a statistical model, develop Monte Carlo simulations to compute approximate statistics and probability distributions for inference and prediction.

Learn and practice how to summarize, interpret and communicate probability distributions and inference results

#interpretingprobabilities : Given a probability distribution or result of an inference procedure, identify its important features and describe them using statistical and non-statistical language.

#summarystatistics : Given a probability distribution or inference procedure, compute and describe the meaning of various summary statistics like mean, standard deviation, and quantiles.

Prerequisites & Working Knowledge

Courses:

CS112: Knowledge: Information-Based Decisions

It would be useful to take this course together with *CS166: Modeling, Simulation, and Decision Making*, where you will gain additional practical experience of the many concepts and techniques learned in this course.

Knowledge prerequisites:

Basic probability and statistics: including the sum and product rules, marginal and conditional probabilities, Bayes' rule, probabilities over discrete and continuous variables. You should read MacKay's *Information theory, inference, and learning algorithms*, Chapter 2 (available for free at http://www.inference.org.uk/itila/book.html) up to the end of Section 2.3, including doing all examples and exercises (there are 11 of them). More practice with basic probability will prepare you even better for the course. Optionally, you can also do Exercises 2.16, 2.21–2.24, 2.31, 2.33, 2.34, 2.36, 2.37. If you are really into statistical data modeling, work through everything in Chapter 2. You won't regret it.

Elementary calculus: derivatives, definite and indefinite integrals of elementary functions.

Matrix and vector algebra.

Skills prerequisites:

Fluency in R for practical statistical analyses is essential. For a practical introduction to basic programming in R, you can take the free coursera course offered by Johns Hopkins University. Also, you can use the RStudio resources cited in https://www.rstudio.com/online-learning/ and the package "swirl" to learn R interactively and by example.

Assignments

Note: Sunday is considered the beginning of the academic week for determining due dates.

Assignment Title	Weighting		Important Dates
Week 1 homework	2x	**Released:** **Due:**	Week 1, Monday Week 1, Saturday
Week 2 homework	2x	**Released:** **Due:**	Week 2, Monday Week 2, Saturday
Week 3 homework	2x	**Released:** **Due:**	Week 3, Monday Week 3, Saturday
Week 4 homework	2x	**Released:** **Due:**	Week 4, Monday Week 4, Saturday
Week 7 homework	2x	**Released:** **Due:**	Week 7, Monday Week 7, Saturday
Week 8 homework	2x	**Released:** **Due:**	Week 8, Monday Week 8, Saturday
LBA	5x	**Released:** **Due:**	Week 6, Friday Week 9, Sunday
Week 9 homework	2x	**Released:** **Due:**	Week 9, Monday Week 9, Saturday
Week 10 homework	2x	**Released:** **Due:**	Week 10, Monday Week 10, Saturday
Week 11 homework	2x	**Released:** **Due:**	Week 11, Monday Week 11, Saturday
Final project	10x	**Released:** **Due:**	Week 12, Monday Week 15, Saturday

Required Texts

Barber, D. (2012). *Bayesian Reasoning and Machine Learning*. Cambridge, UK: Cambridge University Press.

http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/020217.pdf

Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

http://www.inference.org.uk/itila/book.html

Verzani, J. (2002). *SimpleR – Using R for introductory statistics.*

http://www.math.csi.cuny.edu/Statistics/R/simpleR/printable/simpleR.pdf

Schedule of Topics and Readings

This course meets for 2 class sessions each week.

Unit 1: Probability and statistics

This unit covers the elements of data modeling and inference in depth. We work with with common probability distributions, building up to more complex data models where exact inference is still possible. You learn how to update estimates and predictions based on new data, how to compare alternative models to determine which is best, and how to communicate your statistical results effectively.

Session 1.1 :
Modeling under uncertainty

Learning Outcomes

#probabilitytheory : When provided with statements of probability, derive related statements of probability – involving marginal, conditional or joint distributions – using the sum rule, product rule and Bayes' rule.

#interpretingprobabilities : Given a probability distribution or result of an inference procedure, identify its important features and describe them using statistical and non-statistical language.

Readings, Videos, and other preparation resources:

Read Chapter 1 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

Read Chapter 2 up to the end of Section 2.3 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

http://www.inference.org.uk/itila/book.html

Session 1.2 : Single parameter models

Learning Outcomes

#exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

[Continued] #interpretingprobabilities : Given a probability distribution or result of an inference procedure, identify its important features and describe them using statistical and non-statistical language.

Readings, Videos, and other preparation resources:

Read Chapter 2 up to the end of Section 2.7 (Sections 2.8 & 2.9 are optional) of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

Chapters 3 & 23 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

http://www.inference.org.uk/itila/book.html

Session 2.1 : Communicating results

Learning Outcomes

#summarystatistics : Given a probability distribution or inference procedure, compute and describe the meaning of various summary statistics like mean, standard deviation, and quantiles.

#Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

[Continued] #exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

Readings, Videos, and other preparation resources:

Section 6 of Verzani, J. (2002). *SimpleR – Using R for introductory statistics* , pp. 54–6

http://www.math.csi.cuny.edu/Statistics/R/simpleR/printable/simpleR.pdf

Read Section 8 on Probability distributions of An introduction to R. *The R Manuals*. Retrieved from https://cran.r-project.org/doc/manuals/r-release/R-intro.html

https://cran.r-project.org/doc/manuals/r-release/R-intro.html#Probability-distributions

Session 2.2 : Multi-parameter models I

Learning Outcomes

[Continued] #exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

[Continued] #Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

Readings, Videos, and other preparation resources:

Chapter 3 up to the end of Section 3.3 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

Chapters 21 & 24 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

http://www.inference.org.uk/itila/book.html

Session 3.1 :
Probability distributions

Learning Outcomes

#rightdistribution : Given a data set or real-world situation, use standard properties of probability distributions to select appropriate distributions in one or more variables to represent the scenario.

Readings, Videos, and other preparation resources:

Read Chapter 23 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

http://www.inference.org.uk/itila/book.html

NIST/SEMATECH. (2012, April). What is a Probability Distribution, *e-Handbook of Statistical Methods*. Retrieved from http://www.itl.nist.gov/div898/handbook/eda/section3/eda361.htm

http://www.itl.nist.gov/div898/handbook/eda/section3/eda361.htm

(Optional) Khan Academy. (n.d.). *Random variables*. Retrieved from https://www.khanacademy.org/math/ap-statistics/random-variables-ap

https://www.khanacademy.org/math/ap-statistics/random-variables-ap

Session 3.2 :
Conjugate prior distributions

Learning Outcomes

[Continued] #exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

[Continued] #probabilitytheory : When provided with statements of probability, derive related statements of probability – involving marginal, conditional or joint distributions – using the sum rule, product rule and Bayes' rule.

Readings, Videos, and other preparation resources:

Orloff, J., Bloom, J. (2014). Conjugate priors: Beta and normal. *Introduction to Probability and Statistics*. MIT OpenCourseWare.

https://ocw.mit.edu/courses/mathematics/18-05-introduction-to-probability-and-statistics-spring-2014/readings/MIT18_05S14_Reading15a.pdf

Conjugate prior. (n.d.). In *Wikipedia*. Retrieved September 15, 2017, from https://en.wikipedia.org/wiki/Conjugate_prior

https://en.wikipedia.org/wiki/Conjugate_prior#Table_of_conjugate_distributions

Session 4.1 : Normal likelihoods with conjugate priors

Learning Outcomes

#Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

[Continued] #exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

[Continued] #summarystatistics : Given a probability distribution or inference procedure, compute and describe the meaning of various summary statistics like mean, standard deviation, and quantiles.

Readings, Videos, and other preparation resources:

Verzani, J. (2002). *SimpleR – Using R for introductory statistics* , pp. 116–121

https://cran.r-project.org/doc/contrib/Verzani-SimpleR.pdf

Leeper, T.J. (n.d.). The curve function. *Course materials for teaching R*. Retrieved from http://thomasleeper.com/Rcourse/Tutorials/curve.html

http://thomasleeper.com/Rcourse/Tutorials/curve.html

Programiz. (n.d.). R Histogram using hist() function. *Learn R programming: The definitive guide*. Retrieved from https://www.programiz.com/r-programming/histogram

https://www.programiz.com/r-programming/histogram

Session 4.2 : Selecting prior hyperparameters

Learning Outcomes

[Continued] #exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

[Continued] #summarystatistics : Given a probability distribution or inference procedure, compute and describe the meaning of various summary statistics like mean, standard deviation, and quantiles.

Readings, Videos, and other preparation resources:

Goldstick, J.E. (2009). Optimization using the optim function. *Statistics 406: Introduction to Statistical Computing*. University of Michigan. Retrieved from http://dept.stat.lsa.umich.edu/~jasoneg/Stat406/lab10.pdf

http://dept.stat.lsa.umich.edu/~jasoneg/Stat406/lab10.pdf

Limpert, E., Stahel, W.A., Abbt, M. (2001, May). Log-normal distributions across the sciences: Keys and clues. *BioScience, 51*(5), 341–352.

https://stat.ethz.ch/~stahel/lognormal/bioscience.pdf

Log-normal distribution. (n.d.). In *Wikipedia*. Retrieved September 23, 2017, from https://en.wikipedia.org/wiki/Log-normal_distribution

https://en.wikipedia.org/wiki/Log-normal_distribution

Session 5.1 : Hierarchical models I

Learning Outcomes

[Continued] #exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

[Continued] #Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

Readings, Videos, and other preparation resources:

Watch up to 0:22:30 of Gelman, A. (2016, October 25). *Introduction to Bayesian Data Analysis and Stan with Andrew Gelman* [Video file]. Retrieved from https://www.youtube.com/watch?v=T1gYvX5c2sM

https://www.youtube.com/watch?v=T1gYvX5c2sM

Chapter 5 up to the end of Section 5.3 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

Stan Development Team. (2017, June 19). Stan Modeling Language: User's Guide and Reference Manual. Retrieved from https://github.com/stan-dev/stan/releases/download/v2.16.0/stan-reference-2.16.0.pdf

https://github.com/stan-dev/stan/releases/download/v2.16.0/stan-reference-2.16.0.pdf

Session 5.2 : Multinomial likelihoods with conjugate priors

Learning Outcomes

[Continued] #Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

[Continued] #summarystatistics : Given a probability distribution or inference procedure, compute and describe the meaning of various summary statistics like mean, standard deviation, and quantiles.

Readings, Videos, and other preparation resources:

[mathematicalmonk]. (2011, June 25). *Dirichlet distribution* [Video file]. Retrieved from https://www.youtube.com/watch?v=nfBNOWv1pgE

https://www.youtube.com/watch?v=nfBNOWv1pgE

[mathematicalmonk]. (2011, June 25). *Dirichlet-Categorical model* [Video file]. Retrieved from https://www.youtube.com/watch?v=UDVNyAp3T38

https://www.youtube.com/watch?v=UDVNyAp3T38

Stan Development Team. (2017, June 19). *Stan Modeling Language: User's Guide and Reference Manual*. Retrieved from https://github.com/stan-dev/stan/releases/download/v2.16.0/stan-reference-2.16.0.pdf

https://github.com/stan-dev/stan/releases/download/v2.16.0/stan-reference-2.16.0.pdf

Session 6.1 : Fall break

Learning Outcomes

Readings, Videos, and other preparation resources:

Session 6.2 :
Hierarchical models II

Learning Outcomes

[Continued] #Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

[Continued] #rightdistribution : Given a data set or real-world situation, use standard properties of probability distributions to select appropriate distributions in one or more variables to represent the scenario.

[Continued] #exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

Readings, Videos, and other preparation resources:

Sections 3.4 and 3.8 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.
https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

Mercer, A. (2016, September 8). 5 key things to know about the margin of error in election polls. *Pew Research Center*. Retrieved from http://www.pewresearch.org/fact-tank/2016/09/08/understanding-the-margin-of-error-in-election-polls/
http://www.pewresearch.org/fact-tank/2016/09/08/understanding-the-margin-of-error-in-election-polls/

Total survey error. *Roper Center for Public Opinion Research*. Retrieved from https://ropercenter.cornell.edu/support/polling-fundamentals-total-survey-error/
https://ropercenter.cornell.edu/support/polling-fundamentals-total-survey-error/

Session 7.1 :
Central limit theorem

Learning Outcomes

[Continued] #Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

[Continued] #probabilitytheory : When provided with statements of probability, derive related statements of probability – involving marginal, conditional or joint distributions – using the sum rule, product rule and Bayes' rule.

#analyticalapproximation : Given a statistical model, select appropriate analytical approximations and derive rules with closed form solutions for inference and prediction.

Readings, Videos, and other preparation resources:

Balka, J. [jbstatistics]. (2012, December 28). *Introduction to the Central Limit Theorem* [Video file]. Retrieved from https://www.youtube.com/watch?v=Pujol1yC1_A
https://www.youtube.com/watch?v=Pujol1yC1_A

Chapter 4 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.
https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

(Optional) Osgood, B. (2008, July 3). Central Limit Theorem and Convolution [Video file]. *The Fourier Transforms and its Applications*. Stanford University. Retrieved from https://www.youtube.com/watch?v=LA4Uv6PMRTM
https://www.youtube.com/watch?v=LA4Uv6PMRTM

Session 7.2 : Model comparison I

Learning Outcomes

[Continued] #probabilitytheory : When provided with statements of probability, derive related statements of probability – involving marginal, conditional or joint distributions – using the sum rule, product rule and Bayes' rule.

[Continued] #interpretingprobabilities : Given a probability distribution or result of an inference procedure, identify its important features and describe them using statistical and non-statistical language.

[Continued] #summarystatistics : Given a probability distribution or inference procedure, compute and describe the meaning of various summary statistics like mean, standard deviation, and quantiles.

Readings, Videos, and other preparation resources:

Resnick, B. (2017, July 31). What a nerdy debate about p-values shows about science — and how to fix it. *Vox*. Retrieved from https://www.vox.com/science-and-health/2017/7/31/16021654/p-values-statistical-significance-redefine-0005

- https://www.vox.com/science-and-health/2017/7/31/16021654/p-values-statistical-significance-redefine-0005

Read Chapter 28 up to the end of 28.2 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

- http://www.inference.org.uk/itila/book.html

(Optional) Chapter 6 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

- https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

Session 8.1 : Model comparison II

Learning Outcomes

[Continued] #probabilitytheory : When provided with statements of probability, derive related statements of probability – involving marginal, conditional or joint distributions – using the sum rule, product rule and Bayes' rule.

[Continued] #exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

[Continued] #Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

Readings, Videos, and other preparation resources:

Read Sections 3.2–3.3 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

- http://www.inference.org.uk/itila/book.html

Unit 2: Graphical models

Graphical models provide convenient representation of and computation in statistical models, especially complex ones. In this unit you learn how to represent any complex probability distribution as a graph and how to read properties of the distribution from the graph. You also learn about inference algorithms that take advantage of the structure of the graph to simplify computation.

Session 8.2 :
Directed graphical models

Learning Outcomes

#graphicalmodels : Write down a graphical model representation of a joint probability distribution representing a statistical model (or vice versa) and manipulate the graphical notation for simplification, inference and prediction in the model.

Readings, Videos, and other preparation resources:

Sections 8.1–8.3 of Bishop, C. (2006). *Pattern recognition and machine learning.* New York: Springer.

https://www.microsoft.com/en-us/research/wp-content/uploads/2016/05/Bishop-PRML-sample.pdf

Session 9.1 :
Factor graphs

Learning Outcomes

[Continued] #graphicalmodels : Write down a graphical model representation of a joint probability distribution representing a statistical model (or vice versa) and manipulate the graphical notation for simplification, inference and prediction in the model.

Readings, Videos, and other preparation resources:

Section 8.4 of Bishop, C. (2006). *Pattern recognition and machine learning.* New York Springer.

https://www.microsoft.com/en-us/research/wp-content/uploads/2016/05/Bishop-PRML-sample.pdf

Bishop, C.M. (2013). *Graphical Models 1* [Video file]. Retrieved from https://www.youtube.com/watch?v=ju1Grt2hdko

https://www.youtube.com/watch?v=ju1Grt2hdko

Bishop, C.M. (2013). *Graphical Models 2* [Video file]. Retrieved from https://www.youtube.com/watch?v=c0AWH5UFyOk

https://www.youtube.com/watch?v=c0AWH5UFyOk

Session 9.2 :
The sum–product algorithm

Learning Outcomes

[Continued] #graphicalmodels : Write down a graphical model representation of a joint probability distribution representing a statistical model (or vice versa) and manipulate the graphical notation for simplification, inference and prediction in the model.

[Continued] #exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

Readings, Videos, and other preparation resources:

Section 8.4.4 of Bishop, C. (2006). *Pattern recognition and machine learning.* New York: Springer.

🔗 https://www.microsoft.com/en-us/research/wp-content/uploads/2016/05/Bishop-PRML-sample.pdf

Bishop, C.M. (2013). *Graphical Models 2* [Video file]. Retrieved from https://www.youtube.com/watch?v=c0AWH5UFyOk

🔗 https://www.youtube.com/watch?v=c0AWH5UFyOk

(Optional) Bishop, C.M. (2013). *Graphical Models 3* [Video file]. Retrieved from https://www.youtube.com/watch?v=QJSEQeH40hM

🔗 https://www.youtube.com/watch?v=QJSEQeH40hM

Session 10.1 :
Message passing on cyclic graphs

Learning Outcomes

#exactinference : Given a statistical model, use known analytical properties of standard distributions to derive rules for inference and prediction.

#graphicalmodels : Write down a graphical model representation of a joint probability distribution representing a statistical model (or vice versa) and manipulate the graphical notation for simplification, inference and prediction in the model.

Readings, Videos, and other preparation resources:

Sections 8.4.6–8.4.8 of Bishop, C. (2006). *Pattern recognition and machine learning.* New York: Springer.

🔗 https://www.microsoft.com/en-us/research/wp-content/uploads/2016/05/Bishop-PRML-sample.pdf

(Optional) Chapter 6 of Barber, D. (2012). *Bayesian Reasoning and Machine Learning*. Cambridge, UK: Cambridge University Press.

- http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/020217.pdf

(Optional) Bromiley, P.A. (2014). *Products and Convolutions of Gaussian Probability Density Functions*. Retrieved from http://www.tina-vision.net/docs/memos/2003-003.pdf

- http://www.tina-vision.net/docs/memos/2003-003.pdf

Session 10.2 :
Synthesis: Verifying the GPS tracking model

Learning Outcomes

[Continued] #Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

[Continued] #interpretingprobabilities : Given a probability distribution or result of an inference procedure, identify its important features and describe them using statistical and non-statistical language.

[Continued] #summarystatistics : Given a probability distribution or inference procedure, compute and describe the meaning of various summary statistics like mean, standard deviation, and quantiles.

[Continued] #rightdistribution : Given a data set or real-world situation, use standard properties of probability distributions to select appropriate distributions in one or more variables to represent the scenario.

Readings, Videos, and other preparation resources:

Chapter 6 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

- https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

Session 11.1 :
Expectation propagation

Learning Outcomes

#analyticalapproximation : Given a statistical model, select appropriate analytical approximations and derive rules with closed form solutions for inference and prediction.

#graphicalmodels : Write down a graphical model representation of a joint probability distribution representing a statistical model (or vice versa) and manipulate the graphical notation for simplification, inference and prediction in the model.

Readings, Videos, and other preparation resources:

Bishop, C.M. (2013). *Graphical Models 3* [Video file]. Retrieved from https://www.youtube.com/watch?v=QJSEQeH40hM

https://www.youtube.com/watch?v=QJSEQeH40hM

(Optional) Sections 13.7–13.8 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

Section 10.7 of Bishop, C. (2006). *Pattern recognition and machine learning.* New York: Springer.

http://users.isr.ist.utl.pt/~wurmd/Livros/school/Bishop%20-%20Pattern%20Recognition%20And%20Machine%20Learning%20-%20Springer%20%202006.pdf

Session 11.2 :
Case study: The TrueSkill model

Learning Outcomes

[Continued] #analyticalapproximation : Given a statistical model, select appropriate analytical approximations and derive rules with closed form solutions for inference and prediction.

[Continued] #interpretingprobabilities : Given a probability distribution or result of an inference procedure, identify its important features and describe them using statistical and non-statistical language.

[Continued] #graphicalmodels : Write down a graphical model representation of a joint probability distribution representing a statistical model (or vice versa) and manipulate the graphical notation for simplification, inference and prediction in the model.

Readings, Videos, and other preparation resources:

Herbrich, R., Minka, T., Graepel T. (2006). TrueSkill™: A Bayesian Skill Rating System. *Proceedings of the 19th International Conference on Neural Information Processing Systems*, 569–576.

https://www.microsoft.com/en-us/research/wp-content/uploads/2007/01/NIPS2006_0688.pdf

Lee, H. (2016). *TrueSkill — The video game rating system*. Retrieved from http://trueskill.org/

http://trueskill.org/

Unit 3: Approximate inference with Monte Carlo methods

When we cannot do exact inference, as is often the case with messy real-world data, we turn to approximate methods. Monte Carlo simulatuons use random samples to replace intractable integrals with straightforward sums, allowing us to approximate any complex scenario. In this unit you learn how to implement and discuss the convergence properties of a few simple, but powerful Monte Carlo methods.

Session 12.1 : Rejection and importance sampling I

Learning Outcomes

#montecarlo : Given a statistical model, develop Monte Carlo simulations to compute approximate statistics and probability distributions for inference and prediction.

#Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

Readings, Videos, and other preparation resources:

[mathematicalmonk]. (2011, August 9). *Importance sampling — introduction* [Video file]. Retrieved from https://www.youtube.com/watch?v=S3LAOZxGcnk

https://www.youtube.com/watch?v=S3LAOZxGcnk

[mathematicalmonk]. (2011, July 18). *Importance sampling — intuition* [Video file]. Retrieved from https://www.youtube.com/watch?v=3Mw6ivkDVZc

https://www.youtube.com/watch?v=3Mw6ivkDVZc [mathematicalmonk]. (2011, July 18). *Importance sampling without normalization constants* [Video file]. Retrieved from https://www.youtube.com/watch?v=gYvlnu5AAzE

https://www.youtube.com/watch?v=gYvlnu5AAzE

Chapter 10 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

Session 12.2 : Friendsgiving break

Learning Outcomes

Readings, Videos, and other preparation resources:

Session 13.1 : Rejection and importance sampling II

Learning Outcomes

#montecarlo : Given a statistical model, develop Monte Carlo simulations to compute approximate statistics and probability distributions for inference and prediction.

#Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

[Continued] #summarystatistics : Given a probability distribution or inference procedure, compute and describe the meaning of various summary statistics like mean, standard deviation, and quantiles.

Readings, Videos, and other preparation resources:

Chapter 29 up to the end of Section 29.3 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

http://www.inference.org.uk/mackay/itprnn/ps/356.384.pdf

MacKay, D.J.C. (2012). *Lecture 12: Approximating Probability Distributions (II): Monte Carlo Methods (I): Importance Sampling, Rejection Sampling, Gibbs Sampling, Metropolis Method* [Video file]. Retrieved from http://videolectures.net/mackay_course_12/

http://videolectures.net/mackay_course_12/

Session 13.2 : The Metropolis-Hasting algorithm

Learning Outcomes

#montecarlo : Given a statistical model, develop Monte Carlo simulations to compute approximate statistics and probability distributions for inference and prediction.

#Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

Readings, Videos, and other preparation resources:

Section 29.4 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

http://www.inference.org.uk/mackay/itprnn/ps/356.384.pdf

Watch 0:54:00-1:08:20 of MacKay, D.J.C. (2012). *Lecture 12: Approximating Probability Distributions (II): Monte Carlo Methods (I): Importance Sampling, Rejection Sampling, Gibbs Sampling, Metropolis Method* [Video file]. Retrieved from http://videolectures.net/mackay_course_12/

http://videolectures.net/mackay_course_12/

Session 14.1 : Gibbs sampling

Learning Outcomes

#montecarlo : Given a statistical model, develop Monte Carlo simulations to compute approximate statistics and probability distributions for inference and prediction.

#probabilitytheory : When provided with statements of probability, derive related statements of probability - involving marginal, conditional or joint distributions - using the sum rule, product rule and Bayes' rule.

Readings, Videos, and other preparation resources:

Section 29.5 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

- http://www.inference.org.uk/mackay/itprnn/ps/356.384.pdf

Watch 1:08:15–end of MacKay, D.J.C. (2012). *Lecture 12: Approximating Probability Distributions (II): Monte Carlo Methods (I): Importance Sampling, Rejection Sampling, Gibbs Sampling, Metropolis Method* [Video file]. Retrieved from http://videolectures.net/mackay_course_12/

- http://videolectures.net/mackay_course_12/

Niemi, J. (2013, March 3). *Gibbs sampling* [Video file]. Retrieved from https://www.youtube.com/watch?v=a_08GKWHFWo

- https://www.youtube.com/watch?v=a_08GKWHFWo

(Optional) Chapter 11 up to the end of Section 11.3 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

- https://www.amazon.com/Bayesian-Analysis-Chapman-Statistical-Science/dp/1439840954/

(Optional) Section 29.6 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

- http://www.inference.org.uk/mackay/itprnn/ps/356.384.pdf

Session 14.2 :
MCMC sampling in Stan

Learning Outcomes

#montecarlo : Given a statistical model, develop Monte Carlo simulations to compute approximate statistics and probability distributions for inference and prediction.

#Rimplementation : Implement rules derived using exact or approximate methods in R to generate, summarize and present results of inference or prediction in a statistical model.

#summarystatistics : Given a probability distribution or inference procedure, compute and describe the meaning of various summary statistics like mean, standard deviation, and quantiles.

Readings, Videos, and other preparation resources:

Stan Development Team. (2017, June 19). *Stan Modeling Language: User's Guide and Reference Manual*. Retrieved from https://github.com/stan-dev/stan/releases/download/v2.16.0/stan-reference-2.16.0.pdf

https://github.com/stan-dev/stan/releases/download/v2.16.0/stan-reference-2.16.0.pdf

MacKay, D.J.C. (2012). *Lecture 13: Approximating Probability Distributions (III): Monte Carlo Methods (II): Slice Sampling, Hybrid Monte Carlo, Over-relaxation, Exact Sampling* [Video file]. Retrieved from http://videolectures.net/mackay_course_13/

http://videolectures.net/mackay_course_13/

Sections 11.4–11.5 of Gelman, A., et al. (2013). *Bayesian data analysis*, third edition. Boca Raton, Fla: Chapman & Hall/CRC texts in statistical science.

(Optional) Section 29.8–29.10 of MacKay, D. J. C. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.

http://www.inference.org.uk/mackay/itprnn/ps/356.384.pdf

Session 15.1 : Course synthesis

Learning Outcomes

#interpretingprobabilities : Given a probability distribution or result of an inference procedure, identify its important features and describe them using statistical and non-statistical language.

Readings, Videos, and other preparation resources:

Ghahramani, Z. (2016, May 17). *Bayesian Inference Part I* [Video file]. Machine Learning Summer School 2015, Tübingen. Retrieved from https://www.youtube.com/watch?v=kjo9Y_Vrgn4

https://www.youtube.com/watch?v=kjo9Y_Vrgn4

Policies

Professional Behavior

Minerva expects students to follow guidelines of professional behavior. With respect to academics, this means you are required to prepare appropriately for each class and actively participate in them. You should read all assigned materials, watch assigned videos, and complete all assigned pre-class work, including solving assigned problems and answering study guide questions. Because all of our classes are seminars, all students must be prepared to be full participants—to shirk on preparation not only short-changes you, it also undermines the experience for the other students. You are also required to adhere to assignment guidelines and deadlines, and to contact the appropriate administrator promptly should you wish to request an extension. Additional information, and consequences for failing to meet requirements are described below.

Absence Policy

Students are expected to be logged on to the ALF, ready to participate in class, by the class's stated start time. They should arrive a few minutes early to ensure that they have sufficient time to respond to any potential technical issues (see sections below for policies). A student is considered absent if the student arrives more than 2 minutes after the start of class time or leaves at any time during the class session. There will be at least 15 minutes between class meeting times to accommodate restroom breaks.

Excused Absences

There are four categories of formal reasons why students might be excused from missing classes, all of which require documentation:

- religious holidays
- invited participation in an academically significant event, approved in advance by a dean, that directly conflicts with class time (e.g., presenting research at a major conference during class time)
- unforeseen emergencies (e.g., serious medical problems, mental health emergencies, or family emergencies)
- technical or network problems (see section below)

For religious holidays and event participation to be excused, students must submit a request at least 48 hours prior to the session that the student is requesting permission to miss, to arrange the deadline for completing makeup work and, should documentation not already be available, to determine appropriate documentation. If your request is approved, you must submit the agreed-upon documentation no later than 24 hours after returning to class. Documentation may include a letter or email that details the dates and times of the conflict, signed by an appropriate authority (e.g., a clergy member or conference organizer), with contact information. The Excused Absence or Assignment Extension Request Form is available on the registrar site, registrar.minerva.kgi.edu.

For unforeseen emergencies to be excused, a student is required to obtain documentation from a suitable authority (e.g., a doctor or a member of the Student Affairs staff, not RAs), and to submit the documentation no later than 24 hours after returning to class following the absence. The Excused Absence or Assignment Extension Request Form is available on the registrar site, registrar.minerva.kgi.edu. Should there be any difficulty in procuring documentation within 24 hours of returning to class, immediately contact absence@minerva.kgi.edu to report the situation.

All documented absences require make-up work in order to be considered excused. The make-up work is: (a) watch the video recording of the class; and (b) write a 400- to 500-word paper that summarizes how the HCs/LOs covered in the class session were applied in the activities, and that addresses the following questions:

1. What was the most interesting thing you learned from this class session and how does it connect to/expand upon the assigned preparatory material and pre-class work (if applicable)?
2. What aspect of the material covered in this session do you want to explore further and why?
3. What topic in this session did you find most confusing, and how do you plan to address your confusion?

The deadline for make-up work is determined by the designated college dean, with the date set a minimum of one week and a maximum of 1 month from the student's return. Failure to complete satisfactory make-up work will result in the absence being considered a personal absence (see below).

Personal Absences

Students are allowed two personal absences in this course without prior approval or documentation, to allow for mental health days, minor illnesses, emergencies, failure to submit make-up work for documented absences by the deadline, coming late to class or missing any portion of class, incomplete or grossly inadequate pre-class work (see section below), or technology issues that do not meet policies for excused absences (see section below). Although students do not need to formally submit makeup work for these two absences, students are still responsible for completing all readings and other pre-class work, for reviewing the class recordings, and, if necessary, for attending office hours to ensure they understand the HC/LO material presented in classes they missed. Students will not receive any HC or LO scores for the polls and graded activities they missed.

Any unexcused absences beyond the two allowed personal absences will result in a student's being administratively withdrawn from the course. The Student Handbook contains information on the minimum course load required to maintain full-time enrollment status for each semester, and on the consequences for dropping below full-time enrollment.

Pre-Class Work Policy

During classes for which there was specific pre-class work to bring to class, students will be asked to show they have done the work by answering a related poll question, submitting their pre-class work (or some portion of it) as a poll response, or adding their pre-class work into a document in the main classroom or breakout notes. If a student has not completed the pre-class work, or has done so grossly inadequately, faculty will mark the student as absent for that class meeting. This will count as a personal absence. In addition, evidence of grossly inadequate preparation for class, such as failing to complete the assigned readings, may also result in a personal absence at the instructor's discretion.

Late/Missing Assignment Policy

A student may request an official assignment deadline extension for one of the three formal reasons defined in the absence section. The same requirements for advance notice and documentation apply as for absences. The Excused Absence or Assignment Extension Request Form is available on the registrar site, registrar.minerva.kgi.edu.

Students are also allowed three 24-hour personal assignment deadline extensions per course. Multiple 24-hour extensions may be applied to the same assignment. Personal assignment deadline extensions may not be used for final projects (or any assignment due in week 15). Students with a documented emergency that prevented them from submitting a final project by its deadline, and who did not have a short-term extension approved before the deadline, will be administratively withdrawn unless they petition for, and receive, an incomplete from the ASC.

A student without a documented excuse who fails to submit a fully completed assignment that complies with published guidelines by its deadline, beyond their three personal extensions, will be administratively withdrawn from the course.

Policies for Technology and Network Issues

Laptop Repair

Absences due to a student’s failing to repair their personal computer following hardware or software problems will not be eligible for a documented excuse for missing class. As a courtesy, Minerva may provide loaner computers for limited periods of time, which may need to be shared with other students if demand exceeds supply. Absences due to appointments to get a laptop repaired or replaced are not eligible as excused absences.

Students Taking Class at the Residence

Disruptions of class due to widespread technical or network problems (ALF is down, the internet connection at the residence is down, etc.) will not be counted as absences and the product team will work with the academic team to determine any appropriate additional follow-up.

When students are taking class in the residence, they should follow these best practices:

- Restart the computer before class and close unnecessary apps and tabs
- Use the ALF app (as opposed to Chrome)
- Connect via ethernet (turn wifi off)
- Consult tech support immediately for any problems, via live chat if possible, or via email to helpdesk@minerva.kgi.edu in the worst case.

Technical issues that prevent a student from attending class despite following the best practices above will be grounds for the student to be allowed to complete the make-up work necessary for the absence to be excused. A student who has followed best practices but was unable to participate in all or part of class may submit an excused absence request via the Excused Absence or Assignment Extension Request Form, available on the registrar site, registrar.minerva.kgi.edu. Requests must be submitted no later than 24 hours after the class in which the student experienced problems.

Students Taking Class Outside the Residence

Part of the Minerva experience is that the city is our campus and students can take class from a variety of locations. Because we cannot monitor or guarantee the quality of network connections outside the residence, students must perform due diligence when taking class from these locations. There is a larger risk of problems when taking classes on non-Minerva networks; our goal is to set an acceptable level of risk, balancing our interest in students being able to explore the city with our requirement of students being present for and participating in class.

When taking class outside the residence:

- Students must run the A/V connection test while logged in at least 10 minutes prior to class to determine the suitability of the connection. These connection test results are recorded in the database. If the A/V test indicated that the network is high bandwidth, but something goes wrong during class that prevents the student from attending, this will be grounds for the student to be allowed to complete the make-up work necessary for the absence to be excused.
- This type of absence excuse will only be accepted once per student per outside location.
- If a student has repeated problems that interfere with academic performance and class participation due to taking class outside the residence, the product or academic team may notify the student that no further documented excuses will be granted when taking class outside of the residence. Further problems will result in an undocumented absence.

A student who has followed best practices but was unable to participate in all or part of class may submit an excused absence request via the Excused Absence or Assignment Extension Request Form, available on the registrar site, registrar.minerva.kgi.edu. Requests must be submitted no later than 24 hours after the class in which the student experienced problems.

Audio-Only Policy

Technical support staff, the professor, and the ALF system will have the ability to place a student on audio-only mode during class, should the student's bandwidth not be high enough to be on video.

Honor Code

The Minerva Honor Code rests on four pillars: honesty, integrity, mutual respect, and personal responsibility. Minerva students are expected to conduct themselves with the highest levels of these qualities both inside and outside the classroom. Each student serves as an ambassador to the community for Minerva. When one student exhibits inappropriate behavior outside the university, it reflects badly on every student and the institution as a whole (the public tends not to differentiate between individuals in these situations, and attributes bad behavior to the entire student body).

Minerva students are citizens of an academic community whose members are expected to challenge themselves and one another to achieve greatness with honesty, integrity, mutual respect, and personal responsibility. Each individual who joins the Minerva community accepts this commitment in an effort to sustain and enhance personal, professional and institutional reputations.

Principles inherent in this Honor Code include:

- Students shall treat all members of the community with respect and without malicious intent to ensure that all students share equal opportunities.
- Students shall conduct themselves in a manner that upholds their reputation for honesty and integrity in order to promote an environment of trust.

To assist students in understanding their responsibilities under the Honor Code, the following is a list of conduct pertaining to academic matters that violate the Honor Code. Prohibited conduct includes, but is not limited to the following:

Plagiarism

- Knowingly appropriating another's words or ideas and representing them as one's own
- Use of another's words without acknowledging the source
- Paraphrasing the ideas of another without clear acknowledgment of the source
- Falsification or fabrication of a bibliography

Cheating

- Unauthorized collaboration on assignments
- Use of unauthorized resources during class and on coursework

- Use of previously submitted coursework for alternate purposes without prior approval

Obstruction of Honor Code

- Making false statements to an Honor Code investigator

Falsification of Information

- Knowingly making false statements or submitting misleading information related to academic concerns to Minerva faculty or staff
- Submission of falsified documents, such as transcripts, applications, petitions, etc.

It is not a defense to charges of violating this Honor Code for students to claim that they have not received, read or understood this Code, or is otherwise ignorant of its provisions. A student is held to have notice of this Honor Code by enrolling at Minerva. Students must fully cooperate with investigations into potential violations of the Honor Code.

Collaboration policy

We strongly encourage students to discuss the ideas they learn in class with their classmates. Learning in groups is always beneficial. However, although discussing pre-class work or assignments is acceptable, students must produce the work products they submit on their own unless otherwise indicated in the assignment instructions. For essay assignments and research papers, student must always draft their work products independently. Unless otherwise instructed, it is acceptable to give and receive peer feedback on assignments if drafts have been completed by all parties involved in producing and reviewing the work. For all other types of assignments, students may neither look at others' work products, nor share work products with any students who are not acting in an official Minerva capacity as a peer tutor unless indicated in the assignment instructions. For example, while it is acceptable to discuss different approaches to a coding assignment, it is not acceptable to look at another student's code or to share code with a student who is not acting as a peer tutor for the course. In addition to violating the Honor Code, if a student submits an assignment that is not the student's own work, it misrepresents the student's understanding of the concepts, and prevents faculty from giving beneficial feedback.

Students with Disabilities

Students with documented disabilities who would like to request accommodations are asked to submit an Accommodations for Disabilities Request form. The policy, guidelines, request form and other needed documents are found in Prepare at the beginning of each year, and on the Hub in the Student Center under Student Services. Students may request accommodations at any time during the year. The request and documentation are reviewed by our learning disability specialist, who determines whether accommodations are warranted, and contacts the student and assigned faculty members to facilitate all necessary arrangements. Please see the Student Handbook for more details. If you believe that you may have a disability that warrants accommodations but have not yet requested them, please contact Melissa Billings, Student Services Manager, for information (melissa@minerva.kgi.edu) or review the information on the Hub.

Video Recording Policies

In order to provide formative assessment of classroom discussion contributions in context, each Minerva class session will be video recorded. These recordings will be made available to students enrolled in the recorded class section so that students can view the personalized feedback/assessments written by the professor and later review the class discussion. These recordings are not to be shared/distributed by students without the explicit written permission of the course faculty member and college dean overseeing the course.

The video recording of a class section will be made available to the students enrolled in that section shortly after the class, and will remain accessible to the students until the first day of the following academic year. Access to a recording from previous academic years can be requested for the purpose of appealing a grade or selecting video clips to include in a personal academic portfolio. Requests will be reviewed by the dean of the associated college. The Video Access Request Form is available on the registrar site, registrar.minerva.kgi.edu.

Assessment

Assessing Learning Outcomes

Letter grades are based entirely on outcome scores (HCs for Cornerstones or LOs for Cores and Concentrations) assigned using the mastery rubric template.

1-(Lacks knowledge) Does not recall or use the skill or concept when prompted or does so mostly or entirely inaccurately.

2-(Superficial knowledge) Recalls or uses the skill or concept only somewhat accurately or uses the skill or concept in a way that fails to address the relevant problems or goals.

3-(Knowledge) Accurately or effectively uses the skill or concept in a way that addresses the relevant problems or goals.

4-(Deep knowledge) Accurately or effectively uses the skill or concept in a way that addresses the relevant problems or goals and demonstrates a deep grasp of the skill or concept by analyzing, explaining, or justifying the application in a way appropriate to the given context.

5-(Profound knowledge) Uses the skill or concept in a creative and effective way, relying on a novel perspective.

Students will receive HC/LO scores for in-class verbal contributions (approximately one activity a week will be scored), for preparatory assessment poll responses at the beginning of each class, and for reflection poll responses at end of each class. Preparatory assessment polls test understanding of pre-class readings and other assigned materials. Reflection polls provide students with the opportunity to synthesize the in-class activities and summarize a major take-away they learned from class. All in-class scores will have a weight of 1X. HC/LO scores for assignments will typically have a higher weighting, as specified in the Schedule of Assignments.

Grades

Final grades are based on a student's overall performance on Course Objectives (COs). Student performance on each CO is a mean of the weighted Learning Outcome (LO) scores falling under that CO.

Final Course Grades will be determined according to the following scale:

Min Score (≤)	Max Score (<)	Letter G
4.2	5	A+
3.75	4.2	A
3.5	3.75	A-
3.25	3.5	B+
3	3.25	B
2.8	3	B-
2.6	2.8	C+
2.5	2.6	C
2.25	2.5	C-
2	2.25	D
0	2	F

Early Warning Notices

Each semester has a designated grading review period ending after six weeks. At this time, each student's progress will be reviewed by faculty to determine course standing. Students not making adequate progress in the course will be contacted and placed on Early Warning. See the Student Handbook for more details.

HC Grading

All assignments and contributions in class sessions will be graded on application of the HCs using the mastery rubrics. Unprompted HC applications that receive a score of 3 or above will be classified as near or far transfer using criteria established by faculty during the course design process. Assignment and in-class contribution weights apply to HC scores. These scores will impact students' grades in the Cornerstone courses, and will not factor into their grade for this course.

Location-Based Assignment

All Minerva courses include a location-based assignment (LBA). Each location-based assignment involves engaging in an activity in the student's current city of residence, and targets one or more learning outcomes. LBAs require multiple hours of engagement in the city. Analysis, research, or time spent creating the final work product will require additional work. The LBA assignment may be incorporated into an in-class activity.