CONCENTRATION COURSE

# CS156: Machine Learning for Science and Profit

TERM
**Fall 2019**

CREDIT
**4**

## Course Description

Students learn to apply core machine learning techniques — such as classification, perceptron, neural networks, support vector machines, hidden Markov models, and nonparametric models of clustering — as well as fundamental concepts such as feature selection, cross-validation and over-fitting. Students program machine learning algorithms to make sense of a wide range of data, such as genetic data, data used to perform customer segmentation or data used to predict the outcome of elections.

Note: This syllabus is subject to change.

## Course Objectives & Learning Outcomes

### Choose measures appropriate to the task and then compare different models (#modelquality)

**#modelmetrics :** Be able to carefully define and correctly apply the range of common model performance metrics (eg. classification accuracy, recall, precision) and choose metrics appropriate to the task at hand

**#neuralnetworks :** Explain, implement, analyze, and train different neural network architectures (eg feedforward, deep or recurrent) using freely available research tools (such as Keras)

**#overfitting :** Be able to succinctly identify and explain why and when overfitting occurs. Also be able to adopt strategies when appropriate to avoid such pathologies

### Derive and explain different training methods for models. Know the comparative strengths and weaknesses of different methods as well as when the methods are appropriate (#modeltraining)

**#expectationmaximization :** Explain, implement and train the Expectation Maximization algorithm. Be able to show that the method converges to a solution

**#maximumlikelihood :** Explain, implement and train maximum likelihood methods

### Identify the correct paradigm, implement and train a model appropriate to the task (#modelstructure)

**#classification :** Apply and interpret classification methods for a supervised learning task

**#graphicalmodels :** Apply and interpret Bayesian models when expressed as a graphical model

**#regressionalgorithm :** Apply and interpret regression methods for a supervised learning task

**#unsupervisedlearning :** Apply and interpret unsupervised methods for an unsupervised learning task

## Prerequisites & Working Knowledge

CS110: Computation: Solving Problems with Algorithms

CS111A: Continuous Mathematical Systems

CS11B (or else work through the course on Linear Algebra from the Kahn academy: https://www.khanacademy.org/math/linear-algebra)

## Assignments

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

| ASSIGNMENT TITLE | WEIGHTING | | IMPORTANT DATES |
|---|---|---|---|
| Assignment 1 | 2x | **Released:**<br>**Due:** | Week 1, Sunday<br>Week 3, Sunday |
| Assignment 2 | 2x | **Released:**<br>**Due:** | Week 3, Sunday<br>Week 5, Friday |
| Assignment 3 | 2x | **Released:**<br>**Due:** | Week 5, Friday<br>Week 8, Sunday |
| Assignment 4 | 2x | **Released:**<br>**Due:** | Week 8, Sunday<br>Week 10, Friday |
| Assignment 5 | 2x | **Released:**<br>**Due:** | Week 11, Sunday<br>Week 13, Friday |
| LBA - ML | 4x | **Released:**<br>**Due:** | Week 6, Monday<br>Week 14, Friday |
| Final Project | 10x | **Released:**<br>**Due:** | Week 6, Monday<br>Week 15, Friday |

# Required Texts

Barber, D. (2012). *Bayesian reasoning and machine learning*. Cambridge: Cambridge University Press.

http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/181115.pdf

Downey, A. (2013). *Think Bayes*. Beijing: O'Reilly.

http://www.greenteapress.com/thinkbayes/thinkbayes.pdf

(Optional) Bishop, C. M. (2006). *Pattern recognition and machine learning*. New York: Springer.

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

http://www.inference.phy.cam.ac.uk/itila/book.html

# Schedule of Topics and Readings

This course meets for 2 class sessions each week.

## Unit 1: Overview of Machine Learning

Machine learning stands at the intersection of statistics and computer science. It is a greatly promising set of ideas that allow us to extract valuable information from the large volume of data that society is currently producing. In this unit we provide a basic framework we can use to begin to answer some of the more basic questions: What is a machine-learning algorithm? What data are appropriate for a given algorithm? How should we prepare the data and then validate the model afterwards? If we have a model, how do we decide on any actions to take based on the model's output?

### Session 1.1 :
### Introduction and overview of machine learning concepts

**Learning Outcomes**

**#classification :** Apply and interpret classification methods for a supervised learning task

**Readings, Videos, and other preparation resources:**

Read Chapter 1 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

Read Chapter 13 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

(Optional) Read Chapter 1 of Bishop, C. M. (2006). *Pattern recognition and machine learning* . New York: Springer.

Machine Learning: Solving Problems Big, Small, and Prickly. (2016, December 12). Retrieved August 16, 2017, from https://www.youtube.com/watch?v=_rdINNHLYaQ
https://www.youtube.com/watch?v=_rdINNHLYaQ

### Session 1.2 :
### Basic classification and regression

**Learning Outcomes**

**#regressionalgorithm :** Apply and interpret regression methods for a supervised learning task

**[Continued] #classification :** Apply and interpret classification methods for a supervised learning task

**Readings, Videos, and other preparation resources:**

Read Chapter 14 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/181115.pdf

Read Section 17.1 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/181115.pdf

*Net Present Value*. (n.d.). Retrieved August 04, 2017, from http://www.mathsisfun.com/money/net-present-value.html

http://www.mathsisfun.com/money/net-present-value.html

## Session 2.1 :
## Ensuring quality when training

### Learning Outcomes

**#overfitting :** Be able to succinctly identify and explain why and when overfitting occurs. Also be able to adopt strategies when appropriate to avoid such pathologies

**#modelmetrics :** Be able to carefully define and correctly apply the range of common model performance metrics (eg. classification accuracy, recall, precision) and choose metrics appropriate to the task at hand

### Readings, Videos, and other preparation resources:

**Ng, A. (2017) Bias/Variance (C2W1L02). Retrieved January 14, 2018, from https://www.youtube.com/watch?v=SjQyLhQIXSM**

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

Scikit learn documentation, Chapter 3. Model selection and evaluation. (2010). Retrieved February 23, 2017, from http://scikit-learn.org/stable/model_selection.html

http://scikit-learn.org/stable/model_selection.html

(Optional) Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective.* Cambridge: The MIT Press.

- 1.4.7 Overfitting (p.22)
- 1.4.8 Model selection (p.22)
- 6.4.4 The bias-variance tradeoff (p.202)

(Optional) Brohnshtein, A. (2017). Train/Test Split and Cross Validation in Python. Retrieved January 14, 2018, from https://towardsdatascience.com/train-test-split-and-cross-validation-in-python-80b61beca4b6

https://towardsdatascience.com/train-test-split-and-cross-validation-in-python-80b61beca4b6

## Session 2.2 :
## Quantifying model quality

**Learning Outcomes**

**[Continued] #modelmetrics :** Be able to carefully define and correctly apply the range of common model performance metrics (eg. classification accuracy, recall, precision) and choose metrics appropriate to the task at hand

**Readings, Videos, and other preparation resources:**

Domingos, P. (2012). A few useful things to know about machine learning. *Communications of the ACM*, *55*(10) 78-87.

https://homes.cs.washington.edu/~pedrod/papers/cacm12.pdf

Scikit learn documentation, Chapter 3. Model selection and evaluation. (2010). Retrieved February 23, 2017, from http://scikit-learn.org/stable/model_selection.html

http://scikit-learn.org/stable/model_selection.html

(Optional) Murphy, K. (2012). Machine Learning: A Probabilistic Perspective. Cambridge: The MIT Press.

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# Unit 2: Linear models

Linear models are more powerful than one might initially believe. If one has a good idea of the sort of underlying behavior then one can find basis functions that provide a good representation of the desired target function. Linear models do not require that the basis functions are linear; in fact the basis functions can be highly nonlinear. However the models must be linear in their coefficients. This means that we can can optimally fit linear combinations of complex, non-linear functions.

## Session 3.1 :
## Linear parameter models

**Learning Outcomes**

**[Continued] #regressionalgorithm :** Apply and interpret regression methods for a supervised learning task

**Readings, Videos, and other preparation resources:**

(Option 1) Read Sections 17.1 and 17.2 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

Location based assignment instructions

Final project assignment instructions

(Option 2) Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective.* Cambridge: The MIT Press.

(Option 2) Deo, S. (2016) *Learn the Concept of linearity in Regression Models.*
https://www.datasciencecentral.com/profiles/blogs/learn-the-concept-of-linearity-in-regression-models

## Session 3.2 :
## Logistic regression

### Learning Outcomes

**[Continued] #classification :** Apply and interpret classification methods for a supervised learning task

### Readings, Videos, and other preparation resources:

(Option 1) Read Sections 17.4 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

(Option 2) Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective.* Cambridge: The MIT Press.

## Session 4.1 :
## Principal component analysis (PCA)

### Learning Outcomes

**[Continued] #unsupervisedlearning :** Apply and interpret unsupervised methods for an unsupervised learning task

### Readings, Videos, and other preparation resources:

(Option 1) Read sections 15.1-15.3 Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

Starmer, J. (2018). StatQuest: Principal Component Analysis (PCA), Step-by-Step Retrieved January 31, 2018, from https://www.youtube.com/watch?v=FgakZw6K1QQ
https://www.youtube.com/watch?v=FgakZw6K1QQ

(Option 2) Read sections 12.2 and 12.3 of Murphy, K. (2012). Machine Learning: A Probabilistic Perspective. Cambridge: The MIT Press.

## Session 4.2 :
## Fisher's Linear discriminant

**Learning Outcomes**

**[Continued] #classification :** Apply and interpret classification methods for a supervised learning task

**Readings, Videos, and other preparation resources:**

(Option 1) Read Chapter 16 of Barber, D. (2012). *Bayesian reasoning and machine learning*. Cambridge: Cambridge University Press.

(Option 2) Read section 8.6.3 of Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective*. Cambridge: The MIT Press.

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## Unit 3: Probabilistic Learning

Explicitly using probabilities allows us to take principled approaches to learning and making decisions, even if not all the data is observed! They also provide a consistent language (graphical models) which allows easier communication and visualization of a wide variety of models.

## Session 5.1 :
## Bayesian decision theory

**Learning Outcomes**

**[Continued] #classification :** Apply and interpret classification methods for a supervised learning task

**Readings, Videos, and other preparation resources:**

(Option 1) Read sections 7.1 and 7.2 of Barber, D. (2012). *Bayesian reasoning and machine learning*. Cambridg
Cambridge University Press.
http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/181115.pdf

Chorionic villus sampling (Beyond the Basics). (n.d.). Retrieved August 17, 2017, from http://www.uptodate.com/contents/chorionic-villus-sampling-beyond-the-basics
http://www.uptodate.com/contents/chorionic-villus-sampling-beyond-the-basics

(Option 2) Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective. *Cambridge: The MIT Press.

- 2.2.3.1 Example: medical diagnosis (p.29): read through the example as it may help with pre-class work
- 5.7.3.2 Utility theory (p.185): provides a short introduction to utility theory
- 10.6 Influence (decision) diagrams (p.328-331): read the graphical interpretation of decision diagrams up to POMDP.

## Session 5.2 :
## Interpreting graphical models

**Learning Outcomes**

**#graphicalmodels :** Apply and interpret Bayesian models when expressed as a graphical model

**Readings, Videos, and other preparation resources:**

Read sections 8.1 and 8.2 of Bishop, C. M. (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 6.1 :
## Spring break

**Learning Outcomes**

**Readings, Videos, and other preparation resources:**

## Session 6.2 :
## Maximum likelihood learning

**Learning Outcomes**

**#maximumlikelihood :** Explain, implement and train maximum likelihood methods

**Readings, Videos, and other preparation resources:**

Read chapter 3 of Downey, A. (2013). *Think Bayes*. Beijing: O'Reilly.
http://www.greenteapress.com/thinkbayes/thinkbayes.pdf

Brooks-Bartlett, J. (2018). *Probability concepts explained: Maximum likelihood estimation.*
https://towardsdatascience.com/probability-concepts-explained-maximum-likelihood-estimation-c7b4342fdbb1

## Session 7.1 :
## Expectation maximization

**Learning Outcomes**

**#expectationmaximization :** Explain, implement and train the Expectation Maximization algorithm. Be able to show that the method converges to a solution

**Readings, Videos, and other preparation resources:**

(Option 1) Read Sections 11.1 - 11.4 of Barber, D. (2012). *Bayesian reasoning and machine learning*. Cambridge: Cambridge University Press.
🔗 http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/181115.pdf

Do, C. B., & Batzoglou, S. (2008). What is the expectation maximization algorithm?. *Nature biotechnology*, *26*(8), 897.
🔗 http://ai.stanford.edu/~chuongdo/papers/em_tutorial.pdf

(Optional) Chapter 9 of Bishop, C. M. (2006). *Pattern recognition and machine learning*. New York: Springer.

(Option 2) Read section 11.4 of Murphy, K. (2012). Machine Learning: A Probabilistic Perspective. Cambridge: The MIT Press.

(Optional) Iacobelli F (2015). The EM Algorithm. Retrieved from Youtube on 4 November 2019. https://www.youtube.com/watch?v=7e65vXZEv5Q
🔗 https://www.youtube.com/watch?v=7e65vXZEv5Q

## Session 7.2 :
## Bayesian linear models

**Learning Outcomes**

**[Continued] #regressionalgorithm :** Apply and interpret regression methods for a supervised learning task

**Readings, Videos, and other preparation resources:**

(Option 1) Read section 18.1 of Barber, D. (2012). *Bayesian reasoning and machine learning*. Cambridge: Cambridge University Press.
🔗 http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/181115.pdf

(Optional) Mathematicalmonk (2011, June 29). Bayesian Linear Regression. Retrieved August 29, 2017, from https://www.youtube.com/watch?v=dtkGq9tdYcI
🔗 https://www.youtube.com/watch?v=dtkGq9tdYcI

(Option 2) Murphy, K. (2012). Machine Learning: A Probabilistic Perspective. Cambridge: The MIT Press.

Brooks-Bartlett, J. (2018) *Probability concepts explained: Bayesian inference for parameter estimation.*
🔗 https://towardsdatascience.com/probability-concepts-explained-bayesian-inference-for-parameter-estimation-90e8930e5348

Koehrsen, W. (2018) *Introduction to Bayesian Linear Regression.*
https://towardsdatascience.com/introduction-to-bayesian-linear-regression-e66e60791ea7

## Session 8.1 : Gaussian processes

**Learning Outcomes**

**[Continued] #regressionalgorithm :** Apply and interpret regression methods for a supervised learning task

**Readings, Videos, and other preparation resources:**

De Freitas, N. (2013, February 04). Introduction to Gaussian processes. Retrieved September 22, 2017, from https://www.youtube.com/watch?v=4vGiHC35j9s
https://www.youtube.com/watch?v=4vGiHC35j9s

(Optional) Read sections 19.1-19.4 of Barber, D. (2012). *Bayesian reasoning and machine learning*. Cambridge: Cambridge University Press.
http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/181115.pdf

Bailey, K. *Gaussian Processes for Dummies*. Retrieved March 03, 2019, from http://katbailey.github.io/post/gaussian-processes-for-dummies/
http://katbailey.github.io/post/gaussian-processes-for-dummies/

(Optional) Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective*. Cambridge: The MIT Press.

(Optional) Cunningham, J. (2012, July 06). MLSS 2012: J. Cunningham - *Gaussian Processes for Machine Learning (Part 1)*. Retrieved March 03, 2019, from https://www.youtube.com/watch?v=BS4Wd5rwNwE
https://www.youtube.com/watch?v=BS4Wd5rwNwE

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# Unit 4: Support vector machines

Support vector machines are a very successful example of maximum margin learning, in which a classifier is sought that maximizes the distance between two categories. Using the kernel trick one can convert this straightforward idea into a much more powerful classifier that is able to operate in a non-linear high-dimensional space.

## Session 8.2 : Maximum margin learning

**Learning Outcomes**

**[Continued] #classification :** Apply and interpret classification methods for a supervised learning task

**Readings, Videos, and other preparation resources:**

Winston, P. (2014, January 10). Learning: Support Vector Machines. Retrieved September 01, 2017, from https://www.youtube.com/watch?v=_PwhiWxHK8o
https://www.youtube.com/watch?v=_PwhiWxHK8o

(Optional) Read Sections 17.3, and 17.5 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

(Optional) Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective.* Cambridge: The MIT Press.

## Session 9.1 :
## The kernel trick

**Learning Outcomes**

**[Continued] #classification :** Apply and interpret classification methods for a supervised learning task

**Readings, Videos, and other preparation resources:**

Rohrer, B. (2017, September 17). How Support Vector Machines work / How to open a black box [video file].
https://www.youtube.com/watch?v=-Z4aojJ-pdg

(Option 1) Read Sections 17.3 and 17.5.2 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

[3Blue1Brown]. (2016, August 15). Inverse matrices, column space and null space | Essence of linear algebra, chapter 6 [video file].
https://www.youtube.com/watch?v=uQhTuRlWMxw

Ranjan, C. (2017, July 26). Data Science for Mortals - The Kernal Trick [Blog post].
https://dscm.quora.com/The-Kernel-Trick

(Option 2 ) Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective.* Cambridge: The MIT Press.

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# Unit 5: Neural networks

Neural networks are currently undergoing a renaissance as new methods of training them are being discovered. Fundamentally, a neural network is a highly non-linear function parameterized by a large number of coefficients. These coefficients give the functions incredible flexibility, but also make interpreting the model very difficult. This unit will give an overview of the many different neural network architectures and the strengths and weaknesses that they all possess.

## Session 9.2 :
## Feedforward neural networks

### Learning Outcomes

**#neuralnetworks :** Explain, implement, analyze, and train different neural network architectures (eg feedforward, deep or recurrent) using freely available research tools (such as Keras)

### Readings, Videos, and other preparation resources:

(Optional) Read Chapter 5 of Bishop, C. M. (2006). *Pattern recognition and machine learning*. New York: Springer.

Sections 6.1, 6.2, and 6.5 of Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT press. Chicago
http://www.deeplearningbook.org/

## Session 10.1 :
## Deep learning

### Learning Outcomes

**[Continued] #neuralnetworks :** Explain, implement, analyze, and train different neural network architectures (eg feedforward, deep or recurrent) using freely available research tools (such as Keras)

### Readings, Videos, and other preparation resources:

Chapter 6 of Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT press.Chicago
http://www.deeplearningbook.org/

## Session 10.2 :
## Recurrent neural networks

### Learning Outcomes

**[Continued] #neuralnetworks :** Explain, implement, analyze, and train different neural network architectures (eg feedforward, deep or recurrent) using freely available research tools (such as Keras)

### Readings, Videos, and other preparation resources:

Read Chapter 42 of MacKay, D. J. (2003). *Information theory, inference, and learning algorithms*. Cambridge, UK: Cambridge University Press.
http://www.inference.phy.cam.ac.uk/itila/book.html

(Optional) Hopfield, J.J and Tank, D.W., neural Computation of Decision in Optimizations Problems, Biol. Cybern. No. 52
https://www.researchgate.net/publication/19135224_Neural_Computation_of_Decisions_in_Optimization_Pr

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## Unit 6: Clustering models

Clustering model can be trained to reveal interesting insights in data which might not be obvious to the untrained eye.

### Session 11.1 :
### Clustering models

**Learning Outcomes**

**[Continued] #unsupervisedlearning :** Apply and interpret unsupervised methods for an unsupervised learning task

**[Continued] #expectationmaximization :** Explain, implement and train the Expectation Maximization algorithm. Be able to show that the method converges to a solution

**Readings, Videos, and other preparation resources:**

(Option 1) Read Sections 20.1-20.3 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge Cambridge University Press.

Density Estimation. (n.d.). Retrieved October 02, 2017, from http://scikit-learn.org/stable/modules/density.html
http://scikit-learn.org/stable/modules/density.html

(Option 2) Murphy, K. (2012). Machine Learning: A Probabilistic Perspective. Cambridge: The MIT Press.

(Optional) Raval, S. (2017) Gaussian Mixture Models - The Math of Intelligence (Week 7)
https://www.youtube.com/watch?v=JNlEIEwe-Cg

### Session 11.2 :
### Final Project Presentations

**Learning Outcomes**

**[Continued] #regressionalgorithm :** Apply and interpret regression methods for a supervised learning task

**[Continued] #classification :** Apply and interpret classification methods for a supervised learning task

**[Continued] #modelmetrics :** Be able to carefully define and correctly apply the range of common model performance metrics (eg. classification accuracy, recall, precision) and choose metrics appropriate to the task at hand

**Readings, Videos, and other preparation resources:**

## Session 12.1 :
## Topic modeling

**Learning Outcomes**

**[Continued] #unsupervisedlearning :** Apply and interpret unsupervised methods for an unsupervised learning task

**[Continued] #graphicalmodels :** Apply and interpret Bayesian models when expressed as a graphical model

**Readings, Videos, and other preparation resources:**

Chen, E. (n.d.). Introduction to Latent Dirichlet Allocation. Retrieved October 05, 2017, from http://blog.echen.me/2011/08/22/introduction-to-latent-dirichlet-allocation/
http://blog.echen.me/2011/08/22/introduction-to-latent-dirichlet-allocation/

(Optional) Blei, D.; Ng, A.; Jordan, M (2003). "Latent Dirichlet Allocation". *Journal of Machine Learning Research*. **3** (4–5): *pp.* 993–1022.

(Optional) Read Sections 20.6 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

(Optional) Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective.* Cambridge: The MIT Press.

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# Unit 7: Markov models

This unit introduces Markov models, which provide a powerful paradigm for understanding time-series. Hidden Markov models (HMMs) are even more general and can provide insight and predictions for time-series data in which not all the data have been observed. HMMs have been state-of-the-art algorithms in speech recognition for many years.

## Session 12.2 :
## Quinquatria break

**Learning Outcomes**

**Readings, Videos, and other preparation resources:**

## Session 13.1 :
## Markov models

**Learning Outcomes**

**[Continued] #graphicalmodels :** Apply and interpret Bayesian models when expressed as a graphical model

**[Continued] #maximumlikelihood :** Explain, implement and train maximum likelihood methods

**Readings, Videos, and other preparation resources:**

(Option 1) Read Section 23.1 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

(Optional) Read Section 13.1 of Bishop, C. M. (2006). *Pattern recognition and machine learning* . New York: Springer.

Kane, D. *Data Science - Part XIII - Hidden Markov Models* . Retrieved from https://www.youtube.com/watch?v=j3r9a75zOvM
https://www.youtube.com/watch?v=j3r9a75zOvM

(Option 2) Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective* . Cambridge: The MIT Press.

## Session 13.2 :
## Hidden Markov models

**Learning Outcomes**

**[Continued] #graphicalmodels :** Apply and interpret Bayesian models when expressed as a graphical model

**[Continued] #expectationmaximization :** Explain, implement and train the Expectation Maximization algorithm. Be able to show that the method converges to a solution

**Readings, Videos, and other preparation resources:**

(Option 1) Read Sections 23.2-3 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

(Optional) Read Section 13.2 of Bishop, C. M. (2006). *Pattern recognition and machine learning* . New York: Springer.

(Option 2) Murphy, K. (2012). Machine Learning: A Probabilistic Perspective. Cambridge: The MIT Press.

## Session 14.1 :
## Kalman filters

### Learning Outcomes

**[Continued] #regressionalgorithm :** Apply and interpret regression methods for a supervised learning task

**[Continued] #graphicalmodels :** Apply and interpret Bayesian models when expressed as a graphical model

**[Continued] #maximumlikelihood :** Explain, implement and train maximum likelihood methods

### Readings, Videos, and other preparation resources:

Read Chapter 24 of Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.

(Optional) Read Section 13.3 of Bishop, C. M. (2006). *Pattern recognition and machine learning* . New York: Springer.

(Optional) Labbe, R. (n.d.). Kalman and Bayesian Filters in Python. Retrieved October 30, 2017, from http://nbviewer.jupyter.org/github/rlabbe/Kalman-and-Bayesian-Filters-in-Python/blob/master/table_of_contents.ipynb
http://nbviewer.jupyter.org/github/rlabbe/Kalman-and-Bayesian-Filters-in-Python/blob/master/table_of_contents.ipynb

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## Unit 8: Synthesis

This unit is the culmination of the whole course, in which real-world problems are discussed, and potential solutions are explored. Starting from a blank slate, can a suitable model be found and trained? Is the right question being asked? Are there potential privacy issues or fairness issues and are they being appropriately handled?

## Session 14.2 :
## Synthesis

### Learning Outcomes

**[Continued] #classification :** Apply and interpret classification methods for a supervised learning task

**[Continued] #regressionalgorithm :** Apply and interpret regression methods for a supervised learning task

**[Continued] #modelmetrics :** Be able to carefully define and correctly apply the range of common model performance metrics (eg. classification accuracy, recall, precision) and choose metrics appropriate to the task at hand

**Readings, Videos, and other preparation resources:**

Barber, D. (2012). *Bayesian reasoning and machine learning* . Cambridge: Cambridge University Press.
http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/181115.pdf

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# 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 all of 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 if you experience major extenuating circumstances. In such cases we will work with you to complete your work when this is possible. Additional information, and consequences for failing to meet requirements are described below.

## Absence/Tardiness Policy

**Tardiness:** You are expected to be logged on to the Forum, ready to participate in class, by the class's stated start time. You should arrive a few minutes early to ensure that you have sufficient time to respond to any potential technical issues (see sections below for policies). You will be considered late if you miss between 2 and 15 minutes of class in total, and absent if you miss 15 minutes or more of the class session. There will be at least 15 minutes between class meeting times to accommodate restroom breaks. Being late to class *two times* will be counted as an absence. A single late arrival (defined as missing between 2 and 15 minutes of class in total) will have no impact on your absence total, and a third late arrival will not affect the absence total beyond the one undocumented absence accrued after the second late arrival, unless a fourth late arrival occurs; being late 4 times = 2 undocumented absences. Late arrivals to class due to verified technical problems will not be counted. Absences resulting from being late twice to class will not require makeup work.

**Undocumented Excusable Absences:** These absences may be taken at any time and for any reason, without the need to submit documentation of the reason for the absence. Please refer to the table below for the number of undocumented excusable absences allowed based on the type of course. When a student is absent, Forum will record this absence as unexcused. You must submit satisfactory makeup work for each absence for it to become excused (except for an absence due to being late twice as noted above). It is imperative that you do not use up all undocumented absences, as you may need them to cover unforeseen circumstances.

**Documented Excusable Absences due to Extenuating Circumstances**: Students who experience major extenuating circumstances (such as severe illness, injury, family emergency, or personal loss) that could cause them to have more than the allowed undocumented excusable absences may submit supporting documentation using the Documented Absence Request Form, available at registrar.minerva.kgi.edu. Under such circumstances, requests may be submitted whether or not the student has already used their three undocumented excusable absences. Documentation for extenuating circumstances must be from a medical professional, mental health professional (with whom the student has a prior counseling relationship), or other appropriate authority that documents the extenuating circumstance. Student Affairs staff will only provide documentation in instances when they are directly involved in student emergencies and are best-suited to provide it. The Academic Team approver will review and approve or deny the request and, if needed (because of a chronic or major issue), work with you and your instructor(s) to determine the best plan for you to successfully complete your course or courses given your circumstances. All absences approved as eligible to be excused will require makeup work to be submitted by the date designated by the approver.

Minor illnesses and attendance at academic events (such as competitions or conferences) will not be considered extenuating circumstances. For these cases, you must use your undocumented excusable absences and complete the makeup work with the timeframe required.

**Maximum number of absences per course:** Minerva's active learning model means that a student's learning is significantly impacted by their preparation for and engagement/participation in class. Thus, we have instituted a maximum number of class absences a student can accumulate and remain in the course. Please refer to the table below to obtain the maximum number of absences (typically ~25%). Exceeding the absence limit for any reason (both undocumented absences and documented absences due to extenuating circumstances and Religious Holidays) will result in withdrawal from the course (see Student Handbook).

Students who exceed the number of maximum absences for any reason (undocumented or documented) will automatically receive a notice that they will be dropped from the course. There may be consequences to a student's F-1 visa status if the course withdrawal puts the student below 12 units (see Student Handbook for details).

| Course type | Number of undocumented excusable absences | Maximum total number of absences for any reason |
|---|---|---|
| Cornerstone/Core/ Concentration | 3 | 6 |
| Capstone Seminar | 1 | 2 |
| Senior Tutorial/Research Methods | 2 | 3 |

**Make-up work policies for absences:** Make-up work must be submitted no later than 7 days from the absence (by start of class period) using the Makeup Work Submission Form available at registrar.minerva.kgi.edu. If a student needs additional time to complete the makeup work because of an extenuating circumstance, they will need to submit a request using the Assignment & Makeup Work Extension Form at registrar.minerva.kgi.edu. This form must be submitted NO MORE than 5 days from the missing class session to allow time for the extension request to be examined and responded to by Academic staff. Instructors will not be granting makeup work extensions. ALL absences require satisfactory make-up work to be submitted in order to be excused. If an absence results from being late multiple times, work with your professor to determine the appropriate makeup work.

Instructors will review the submitted make-up work and if adequate will convert the unexcused absence into an excused absence in Forum. They may provide a few sentence response in the google doc submission to provide succinct qualitative feedback on what learning the student did or did not demonstrate in their make-up work submission. Some instructors may choose instead to use a rubric score for feedback, but these are not incorporated into a student's grade for the class. Accumulating unexcused absences past the deadline of 7 days, without official approval of an extension is a policy violation and will result in sanctions ranging from Academic Warning (first time offense), Academic Probation, to Administrative Withdrawal from the course (see Student Handbook). Students will not receive a grade for any course that has outstanding unexcused absences.

The make-up work is:

1. Do all the assigned reading and pre-class work and watch the video recording of the class.
2. Answer the reflection poll question.
3. Submit pre-class work with your submission. (If no pre-class work is required for missed session, then a screenshot of Forum indicating "no pre-class work" from that session on the Forum should be submitted.
4. As determined by your professor (often at the end of this syllabus).

In rare cases where the class video is unavailable, the student should explain how the assigned pre-class readings and resources address the HC(s) or LO(s) that are the focus of the session (in addition to submitting the pre-class work, if applicable).

# 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 an undocumented absence (no makeup work will be required). In addition, evidence of grossly inadequate preparation for class, such as failing to complete the assigned readings as demonstrated in class discussions, may also result in an undocumented absence at the instructor's discretion.

# Assignment Submission Policy

Students are allowed four 24-hour personal assignment deadline extensions per course. Multiple 24-hour extensions may be applied to the same assignment, but no more than 4 total are allowed per course. This policy allows students substantial flexibility for cases in which multiple courses have the same or similar major assignment deadlines. Assignment extensions may not be used for final projects, any other assignment due in week 15, or any substantial assignment so designated in the assignment instructions.

Exceeding personal extensions above 4 (four) will result in sanctions of academic standing, and above 8 (eight) will result in administrative withdrawal from this course. Administrative withdrawals may have direct financial or other consequences.

Make sure to allow for enough time to submit the assignment by the deadline, as assignments are time-stamped and one minute late is equivalent to one personal deadline extension. It is recommended to submit assignments at least 15 minutes before a deadline, particularly if you are submitting a large file and/or have potentially reduced internet service.

**Assignment Extensions:** Students who experience major extenuating circumstances (such as severe illness, injury, family emergency, or personal loss) that cause them to need an extension on assignments must submit the Assignment & Makeup Work Extension Form, available at registrar.minerva.kgi.edu. All requested assignment extensions requirement submission and approval via the Assignment & Makeup Work Extension Form, including those with disability accommodations. Some assignments are not eligible for extension (i.e. Final projects, etc.), as well as other assignments as designated in your course syllabus.

**Note**: Students will not receive a passing grade in a course unless ALL work is submitted. Failure to submit the final assignment or any other assignment so designated within the syllabus, without obtaining approval for an Incomplete will result in an F for the course (see Student Handbook). Same policy applies if assignments are not submitted by mutually agreed upon deadline for incomplete submissions.

# Academic Standing

If students exceed personal absences, allotted extensions, or submit late makeup work they will be subject to sanctions in academic standing (see Student Handbook).

# Religious Holidays

Minerva Schools at KGI uses the CUC Holy Days Calendar as the official source for important religious holidays. Students wishing to miss classes to observe one or more of these holidays on this official listing will need to request such absences a minimum of two weeks in advance of the holiday, using the form at the registrar site, which does not require any additional documentation. The Assignment Extension Form may also be used to request short assignment extensions if observance of the holiday requires that the student not perform work. Make-up work will be required for all absences and must be submitted within the required 7 days after the absence (sooner is better). Students who do not specifically request absences due to religious holidays may use one or more of their undocumented excused absences for such purposes. Absences due to religious holidays will count toward the maximum number of absences allowed per course. This does not pose a problem with Cornerstone, Core, and Concentration courses given that the maximum number of absences (6) allowed exceeds the typical number of holy day observances for the listed religions. Courses such as Capstone Seminar, Tutorials and Research Methods, which meet less often and have fewer maximum absences could present a problem. If this situation arises, the student should immediately contact the registrar. Possible solutions may involve rescheduling a tutorial class session to accommodate the holiday or shifting the student temporarily to a different section of the course that meets at a time that is not in conflict with observance of the religious holiday.

# Review by Academic Standards Committee

Students whose cases are referred to the Academic Standards Committee may be subject to the following consequences, depending on the circumstances:

- Academic Warning (first time offense)
- Academic Probation
- Administrative Withdrawal from the course

See the Student Handbook for further details.

# Incomplete Petitions

Students with documented extenuating circumstances that may prevent completion of ALL makeup work and assignments by the last day of the semester must petition for an incomplete from the Academic Standards Committee by no later than Friday of week 15 using the Incomplete Petition form, available at registrar.minerva.kgi.edu. Students who are denied an incomplete (or who fail to petition for an Incomplete) and who do not turn in their assignment will receive a F for the course. Further details may be found in the Student Handbook.

# 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 documented excusable absences.

## Students Taking Class at the Residence

Disruptions of class due to widespread technical or network problems at designated Minerva locations (Forum 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 Forum 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.

If a student is marked late, makeup work is not required. If they are marked absent, the makeup work will be due within a week (see policy detailed above). A student who has followed best practices but was unable to participate in all or part of class may submit an excusable absence request via the Technical Excuse 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 absence will not count toward the students 3 undocumented excusable absences. The student must complete make-up for this absence to be excused and it will count toward the maximum number of absences allowed in the course.
- 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 a Technical Excuse 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 Forum 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 the principles 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. A more detailed guide for avoiding these violations can be found here.

Prohibited conduct includes, but is not limited to the following:

Plagiarism

- Knowingly appropriating another's words, ideas, data or code and representing them as one's own
- Use of another's words, ideas, data or code without acknowledging the source
- Paraphrasing the words and ideas of another without clear acknowledgment of the source
- Modifying the code 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
- Falsification of data for a class session or assignment

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 matters to Minerva faculty or staff
- Fabrication of data on assignments
- 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 are 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 or teaching assistant 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 accommodations are granted, it is the student's responsibility to adhere to all form submissions and required deadlines.

# 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, 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. Students will typically receive at least one score per class session on either one of the polls or activities. 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 in all upper-level courses are based on a student’s overall performance on Course Objectives (COs), which is calculated by taking the mean of all course 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 Grade |
|---|---|---|
| 4 | 5 | A+ |
| 3.55 | 4 | A |
| 3.35 | 3.55 | A- |
| 3.15 | 3.35 | B+ |
| 2.95 | 3.15 | B |
| 2.75 | 2.95 | B- |
| 2.6 | 2.75 | C+ |
| 2.5 | 2.6 | C |
| 2.25 | 2.5 | C- |
| 2 | 2.25 | D |
| 1 | 2 | F |

**Make-up work policies for absences:** Make-up work must be submitted no later than 7 days from the absence (by start of class period) using the Makeup Work Submission Form available at registrar.minerva.kgi.edu. If a student needs additional time to complete the makeup work because of an extenuating circumstance, they will need to submit a request using the Assignment & Makeup Work Extension Form at registrar.minerva.kgi.edu. This form must be submitted NO MORE than 7 days from the missing class session to allow time for the extension request to be examined and responded to by Academic staff. Instructors will not be granting makeup work extensions. ALL absences require satisfactory make-up work to be submitted in order to be excused. If an absence results from being late multiple times, work with your professor to determine the appropriate makeup work.

The **make-up work** for this course is:

1. Do all the assigned reading and pre-class work and watch the video recording of the class.
2. Answer the reflection poll question.
3. Submit pre-class work with your submission. If no pre-class work is required for missed session, then a screenshot of Forum indicating “no pre-class work” from that session on the Forum should be submitted.
4. The breakout problem-solving sessions are a crucial aspect of this course, and the makeup work for an absence reflects this. To make-up a session of this course you must watch the video, then turn in your own solutions to the main material section and a 200 word written summary of the lesson that addresses at least one of the following questions:

   A. What was the most surprising way in which the recorded group solved a problem? How would you have done it differently?

B. In what ways were a group's solution(s) incorrect, or not communicated effectively?

C. What were the most informative comments by either students or the professor during a breakout group?