BMEG 591T: Machine Learning in Medicine

2025/26W Syllabus

COURSE INFORMATION

Instructor:	Hossein Farahani
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Office Hours & Location:	By appointment Office: School of Biomedical Eng. Room 5015

LECTURE DATES | TIMES | ROOMS

Lecture:	Monday 2:00 - 4:30pm UBCV | Gordon B. Shrum Building (SHRM) | Floor: 1 | Room: 1002
Discovery Sessions:	Friday 12:00 – 1:00 pm UBCV | Gordon B. Shrum Building (SHRM) | Floor: 1 | Room: 1002

COURSE DESCRIPTION

This course is structured around three interconnected modules that highlight the breadth of machine learning applications in healthcare: **Deep Learning Fundamentals and Medical Imaging**, **Language Models (LLMs)**, and **Genomics**. In the first module, students will learn foundational concepts in neural networks and their application to medical imaging tasks such as classification and segmentation. The second module focuses on large language models, exploring how LLMs can be leveraged to analyze clinical text data for tasks like clinical text mining. Finally, the third module covers the key principles and workflows for applying ML to genomic data, addressing topics such as variant calling, gene expression analysis, and drug discovery. Through lectures, hands-on coding projects, and real-world case studies, students will develop both the technical competencies and domain-specific insights needed to build effective, ethically sound ML solutions in modern healthcare settings.

LEARNING OBJECTIVES

By the end of the course, you will be able to:

- Explain fundamental concepts of neural networks and deep learning, including SGD, backpropagation, and regularization.
- Apply and interpret appropriate evaluation metrics (accuracy, precision, recall, F1-score, AUC) in medical machine learning applications.
- Implement and evaluate CNN-based architectures for medical image classification, and apply transfer learning strategies.
- Utilize U-Net and 3D U-Net to perform image segmentation tasks, and develop strategies to address common challenges in medical deep learning (small datasets, class imbalance, overfitting).
- Describe Transformer networks (including Vision Transformers, ViT) and implement ViT for image segmentation.
- Apply Generative Adversarial Networks (GANs) for data augmentation and synthetic image generation in biomedical contexts.
- Demonstrate proficiency in implementing and debugging deep learning models through hands-on coding exercises with real medical datasets.
- Outline essential NLP concepts for biomedical applications, including representation methods (e.g., word2vec, BioWordVec).
- Use pre-trained transformers (e.g., BioBERT) for biomedical text mining and analysis.
- Employ dimensionality reduction techniques (e.g., t-SNE) to visualize and interpret high-dimensional genomic data.
- Implement machine learning pipelines for genomic data processing (e.g., variant calling, gene expression analysis).
- Model DNA/RNA sequences using RNNs, LSTMs, and Transformers.
- Examine the protein folding problem and the role of AlphaFold in structural biology.
- Discuss deep learning applications in drug discovery, including lead identification and optimization.
- Evaluate the ethical implications and explain the importance of model interpretability in medical AI applications.
- Design multimodal fusion strategies to integrate imaging, genomic, and clinical text data for improved patient prognosis.

COURSE ORGANIZATION / STRUCTURE

BMEG 591T Course Structure

BMEG 591T will be conducted in-person, adhering to the course schedule of 3 hours per week. Each session will be divided into two parts: a lecture and a **Discovery Session**.

Discovery Sessions

These sessions will always include a *Hands-On Coding & Data Exploration Lab*, where students develop code and analyze datasets relevant to the lecture topic. Additionally, some discovery sessions will feature student presentations of research papers related to the lecture topic, delivered by volunteer presenters.

Team Projects

Students will work in teams of two on data analysis projects. By Week 5, each team must propose a project title and obtain approval in a one-on-one meeting with the instructor. If a proposed project is deemed irrelevant to the course objectives or infeasible, the instructor will provide an alternative project.

Final Project Presentation and Report

For the final project, each team will record a 10-minute presentation and submit it alongside their final project report by the designated deadline.

STUDENT EVALUATION

Evaluation Method	Percentage of Final Grade
Data analysis assignments (2 in total)	30%
*Quizzes (6 bi-weekly in-class sessions via iClicker; best 5 scores count))	10%
Participation in discussions	5%
Project progress report	5%
Final project report	40%
Final project presentation	10%
TOTAL	**100%**

** To accommodate occasional absences, illness, or technical issues, the lowest quiz score will be automatically dropped. As such, there will be no make-up quizzes for missed classes.*

LATE POLICY

10% will be deducted from the mark of assignments submitted late for each day after the submission deadline, up to a maximum of 30%. Work submitted more than 3 days after the deadline will receive a mark of 0.

Nonetheless, students are encouraged and expected to assist each other through the online forum. This is not a place for posting answers, but instead it should be used for solving specific problems/errors people are encountering or providing links to resources. You should not solicit or provide answers to assignment questions. A rule of thumb is that if the answer to the question would make a part of the assignment trivial, it is unacceptable.

The class policies on re-grading of marked work and on both late submission and missed in-class assessments (in accordance with the Academic Calendar language on Grading Practices)

COURSE SCHEDULE

Week	Topic	Assignment
Lecture 1 Jan 5	**Introduction and ML Fundamentals** • Course objectives and structure • Supervised vs. unsupervised learning • Regression, classification, clustering • Cross-validation • Evaluation metrics in medical ML: accuracy, precision, recall, F1-score, AUC • Survival analysis	
Jan 9	**Discovery session:** Hands-On Coding & Data Exploration Lab	
Lecture 2 Jan 12	Artificial neural networks • Neural networks overview • Multilayer perceptron and activation functions • Stochastic gradient descent and back propagation	Quiz 1

	• Loss curves and model evaluation • Challenges and explainability in medical settings	
Jan 16	**Discovery session:** Hands-On Coding & Data Exploration Lab	
Lecture 3 Jan 19	Convolutional neural networks • Convolution and detecting image features • Padding and pooling • Basic building blocks of convolutional neural networks • LeNet -5 architecture • AlexNet architecture • ResNet, VGG-19 • Transfer learning in image classification • Overview of explainability techniques like Grad-CAM in medical imaging	
Jan 23	**Discovery session:** Hands-On Coding & Data Exploration Lab	

Lecture 4
Jan 26
	Deep learning and medical imaging
	• Challenges (overfitting, small datasets, class imbalance)
	• Data preprocessing and augmentation (medical-specific techniques).
	• Image segmentation
	  ○ U-Net architecture.
	  ○ 3D U-Net for volumetric data.
	• Case studies and applications (e.g., tumor segmentation, organ delineation).
		Quiz 2

Jan 30	**Discovery session:** Hands-On Coding & Data Exploration Lab	
Lecture 5 Feb 2	Generative Adversarial Networks (GANs) • Adversarial training principles: Generator vs. Discriminator dynamics. • GAN Variants: CycleGAN for unpaired image-to-image translation (e.g., MRI to CT) and Conditional GANs. • Introduction to Diffusion Models: Denoising Diffusion Probabilistic Models (DDPMs) and Latent Diffusion. • Model Comparison: GANs (training instability, mode collapse) vs. Diffusion (stable training, high fidelity). • Biomedical applications: Synthetic data augmentation for rare diseases and anomaly detection.	• Define title of term project.
Feb 6	**Discovery session:** Hands-On Coding & Data Exploration Lab	

Lecture 6
Feb 9
	• Overview of Natural Language Processing (NLP) in Medicine
	• Challenges in biomedical NLP
	• Representation methods:
	  ○ Bag-of-Words, TF-IDF.
	  ○ Word embeddings (Word2Vec, GloVe).
	• Biomedical embeddings (BioWordVec).
	• Legacy Models (brief): RNNs, LSTMs
		Quiz 3

Feb 13	**Discovery session:** Hands-On Coding & Data Exploration Lab	
	Midterm break Feb 16-20	
Lecture 7 Feb 23	Transformer networks • Attention mechanisms • Self-attention • Multi-head attention • Positional encoding • Feedforward layers • Overall transformer architecture • Transformers vs. CNNs in Medical Imaging tasks	• Homework 1 released.
Feb 27	**Discovery session:** Hands-On Coding & Data Exploration Lab	
Lecture 8 March 2	Biomedical Large Language Models (LLMs) • Pretrained transformer models: ○ General-purpose (BERT, GPT). ○ Biomedical-specific (BioBERT, ClinicalBERT, BlueBERT). ○ Biomedical use cases (e.g., Clinical Text Mining, Clinical decision support systems).	Quiz 4
March 6	**Discovery session:** Hands-On Coding & Data Exploration Lab	
Lecture 9 March 9	Vision transformers (ViT) • Motivation for vision transformers • Patch embedding • Self-attention in ViT • Comparison with CNNs • ViT for medical image segmentation	• Homework 1 due date
March 13	**Discovery session:** Hands-On Coding & Data Exploration Lab	
Lecture 10 March 16	• Overview of genomics and sequencing technologies. • Challenges in genomic data processing. • Feature extraction from genomic data (e.g., SNPs, gene expression). • Dimensionality reduction: PCA, t-SNE, UMAP.	• Quiz 5 • Homework 2 released. • Term project progress report (1-2 pages).
March 20	**Discovery session:** Hands-On Coding & Data Exploration Lab	
Lecture 11 March 23	• Applications of RNNs, LSTMs, and Transformers in DNA/RNA sequence modeling • Use case: Predicting gene expression levels from DNA sequences • CNNs for variant calling (e.g., DeepVariant). • Genome-Wide Association Studies (GWAS) with deep learning.	
March 27	**Discovery session:** Hands-On Coding & Data Exploration Lab	
Lecture 12 March 30	• Protein folding problem and AlphaFold. • Deep learning for drug discovery (screening, target interaction, molecular design). • Case study: AI in COVID-19 drug discovery. • Ethical Considerations in Genomics and AI	• Quiz 6 • Homework 2 due date.
April 3	Holiday	
Lecture 13	Multimodal Learning in Healthcare	

April 6	• Fusion Strategies (Early vs. Late vs. Joint) • Contrastive Learning (CLIP, MedCLIP) • Cross-Modal Attention & VQA • Integration of Genomics & Pathology for Prognosis	
April 10	**Discovery session:** Hands-On Coding & Data Exploration Lab	

COURSE MATERIALS

RECOMMENDED PAPERS:

Below is a curated list of papers categorized by the weekly topics covered in class. These readings are designed to deepen your understanding of the subjects discussed.

Lecture 2: Artificial Neural Networks

1. Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning internal representations by error propagation, parallel distributed processing, explorations in the microstructure of cognition, ed. de rumelhart and j. mcclelland. vol. 1. 1986. *Biometrika*, *71*(599-607), 6.
2. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539
3. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., Van Der Laak, J. A. W. M., Van Ginneken, B., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, *42*, 60–88. https://doi.org/10.1016/j.media.2017.07.005
4. Pandey, B., Kumar Pandey, D., Pratap Mishra, B., & Rhmann, W. (2022). A comprehensive survey of deep learning in the field of medical imaging and medical natural language processing: Challenges and research directions. *Journal of King Saud University - Computer and Information Sciences*, *34*(8), 5083–5099. https://doi.org/10.1016/j.jksuci.2021.01.007

Lecture 3: Convolutional Neural Networks

5. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM*, *60*(6), 84–90. https://doi.org/10.1145/3065386
6. Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278–2324. https://doi.org/10.1109/5.726791

Lecture 4: Deep Learning & Medical Imaging

7. Ronneberger, O., Fischer, P., & Brox, T. (2015). *U-Net: Convolutional Networks for Biomedical Image Segmentation* (No. arXiv:1505.04597). arXiv. https://doi.org/10.48550/arXiv.1505.04597
8. Çiçek, Ö., Abdulkadir, A., Lienkamp, S. S., Brox, T., & Ronneberger, O. (2016). 3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation. In S. Ourselin, L. Joskowicz, M. R. Sabuncu, G. Unal, & W. Wells (Eds.), *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016* (Vol. 9901, pp. 424–432). Springer International Publishing. https://doi.org/10.1007/978-3-319-46723-8_49

Lecture 5: Generative Adversarial Networks (GANs)

9. Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). *Generative Adversarial Networks* (No. arXiv:1406.2661). arXiv. https://doi.org/10.48550/arXiv.1406.2661
10. Mirza, M., & Osindero, S. (2014). *Conditional Generative Adversarial Nets* (No. arXiv:1411.1784). arXiv. https://doi.org/10.48550/arXiv.1411.1784
11. Ho, J.; Jain, A.; Abbeel, P. Denoising Diffusion Probabilistic Models. *Advances in neural information processing systems* **2020**, *33*, 6840–6851.

Lecture 6: Overview of NLP in Medicine

12. Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). *Efficient Estimation of Word Representations in Vector Space* (No. arXiv:1301.3781). arXiv. https://doi.org/10.48550/arXiv.1301.3781
13. Wang, C., Li, M., He, J., Wang, Z., Darzi, E., Chen, Z., Ye, J., Li, T., Su, Y., Ke, J., Qu, K., Li, S., Yu, Y., Liò, P., Wang, T., Wang, Y. G., & Shen, Y. (2024). *A Survey for Large Language Models in Biomedicine* (No. arXiv:2409.00133). arXiv. https://doi.org/10.48550/arXiv.2409.00133
14. Yang, R., Tan, T. F., Lu, W., Thirunavukarasu, A. J., Ting, D. S. W., & Liu, N. (2023). Large language models in health care: Development, applications, and challenges. *Health Care Science*, *2*(4), 255–263. https://doi.org/10.1002/hcs2.61

Lecture 7: Transformer Networks

15. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). *Attention is All you Need*, In Advances in Neural Information Processing Systems (pp. 5998–6008).

Lecture 8: Transformers & Biomedical LLMs

16. Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding* (No. arXiv:1810.04805). arXiv. https://doi.org/10.48550/arXiv.1810.04805
17. Huang, K., Altosaar, J., & Ranganath, R. (2020). *ClinicalBERT: Modeling Clinical Notes and Predicting Hospital Readmission* (No. arXiv:1904.05342). arXiv. https://doi.org/10.48550/arXiv.1904.05342
18. Lee, J., Yoon, W., Kim, S., Kim, D., Kim, S., So, C. H., & Kang, J. (2020). BioBERT: A pre-trained biomedical language representation model for biomedical text mining. *Bioinformatics*, *36*(4), 1234–1240. https://doi.org/10.1093/bioinformatics/btz682

Lecture 9: Vision Transformers (ViT)

19. Chen, J., Lu, Y., Yu, Q., Luo, X., Adeli, E., Wang, Y., Lu, L., Yuille, A. L., & Zhou, Y. (2021). *TransUNet: Transformers Make Strong Encoders for Medical Image Segmentation* (No. arXiv:2102.04306). arXiv. https://doi.org/10.48550/arXiv.2102.04306
20. Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., & Houlsby, N. (2021). *An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale* (No. arXiv:2010.11929). arXiv. https://doi.org/10.48550/arXiv.2010.11929

Lecture 10: Genomics Overview & Dimensionality Reduction

21. Eraslan, G., Avsec, Ž., Gagneur, J., & Theis, F. J. (2019). Deep learning: New computational modelling techniques for genomics. *Nature Reviews Genetics*, *20*(7), 389–403. https://doi.org/10.1038/s41576-019-0122-6
22. Becht, E., McInnes, L., Healy, J., Dutertre, C.-A., Kwok, I. W. H., Ng, L. G., Ginhoux, F., & Newell, E. W. (2019). Dimensionality reduction for visualizing single-cell data using UMAP. *Nature Biotechnology*, *37*(1), 38–44. https://doi.org/10.1038/nbt.4314
23. Kobak, D., & Linderman, G. C. (2021). Initialization is critical for preserving global data structure in both t-SNE and UMAP. *Nature biotechnology*, *39*(2), 156-157.
24. Kobak, D., & Berens, P. (2019). The art of using t-SNE for single-cell transcriptomics. *Nature Communications*, *10*(1), 5416. https://doi.org/10.1038/s41467-019-13056-x

Lecture 11: Advanced Genomic Modeling

25. Poplin, R., Chang, P.-C., Alexander, D., Schwartz, S., Colthurst, T., Ku, A., Newburger, D., Dijamco, J., Nguyen, N., Afshar, P. T., Gross, S. S., Dorfman, L., McLean, C. Y., & DePristo, M. A. (2018). A universal SNP and small-indel variant caller using deep neural networks. *Nature Biotechnology*, *36*(10), 983–987. https://doi.org/10.1038/nbt.4235
26. Sun, T., Wei, Y., Chen, W., & Ding, Y. (2020). Genome-wide association study-based deep learning for survival prediction. *Statistics in medicine*, *39*(30), 4605-4620.
27. Zou, J., Huss, M., Abid, A., Mohammadi, P., Torkamani, A., & Telenti, A. (2019). A primer on deep learning in genomics. *Nature Genetics*, *51*(1), 12–18. https://doi.org/10.1038/s41588-018-0295-5

28. Pipoli, V., Cappelli, M., Palladini, A., Peluso, C., Lovino, M., & Ficarra, E. (2022). Predicting gene expression levels from DNA sequences and post-transcriptional information with transformers. *Computer Methods and Programs in Biomedicine*, *225*, 107035. https://doi.org/10.1016/j.cmpb.2022.107035
29. Novakovsky, G., Dexter, N., Libbrecht, M. W., Wasserman, W. W., & Mostafavi, S. (2023). Obtaining genetics insights from deep learning via explainable artificial intelligence. *Nature Reviews Genetics*, *24*(2), 125–137. https://doi.org/10.1038/s41576-022-00532-2
30. Yue, T., Wang, Y., Zhang, L., Gu, C., Xue, H., Wang, W., Lyu, Q., & Dun, Y. (2023). Deep Learning for Genomics: From Early Neural Nets to Modern Large Language Models. *International Journal of Molecular Sciences*, *24*(21), 15858. https://doi.org/10.3390/ijms242115858

Lecture 12: Protein Folding & Drug Discovery

31. Abramson, J., Adler, J., Dunger, J., Evans, R., Green, T., Pritzel, A., Ronneberger, O., Willmore, L., Ballard, A. J., Bambrick, J., Bodenstein, S. W., Evans, D. A., Hung, C.-C., O'Neill, M., Reiman, D., Tunyasuvunakool, K., Wu, Z., Žemgulytė, A., Arvaniti, E., … Jumper, J. M. (2024). Accurate structure prediction of biomolecular interactions with AlphaFold 3. *Nature*, *630*(8016), 493–500. https://doi.org/10.1038/s41586-024-07487-w
32. Chan, H. C. S., Shan, H., Dahoun, T., Vogel, H., & Yuan, S. (2019). Advancing Drug Discovery via Artificial Intelligence. *Trends in Pharmacological Sciences*, *40*(8), 592–604. https://doi.org/10.1016/j.tips.2019.06.004
33. Keshavarzi Arshadi, A., Webb, J., Salem, M., Cruz, E., Calad-Thomson, S., Ghadirian, N., Collins, J., Diez-Cecilia, E., Kelly, B., Goodarzi, H., & Yuan, J. S. (2020). Artificial Intelligence for COVID-19 Drug Discovery and Vaccine Development. *Frontiers in Artificial Intelligence*, *3*, 65. https://doi.org/10.3389/frai.2020.00065

Lecture 13: Multimodal Learning in Healthcare

34. Acosta, J. N.; Falcone, G. J.; Rajpurkar, P.; Topol, E. J. Multimodal Biomedical AI. *Nature medicine* **2022**, *28* (9), 1773–1784.
35. Radford, A.; Kim, J. W.; Hallacy, C.; Ramesh, A.; Goh, G.; Agarwal, S.; Sastry, G.; Askell, A.; Mishkin, P.; Clark, J.; others. Learning Transferable Visual Models from Natural Language Supervision. In *International conference on machine learning*; PmLR, 2021; pp 8748–8763.
36. Wang, Z.; Wu, Z.; Agarwal, D.; Sun, J. Medclip: Contrastive Learning from Unpaired Medical Images and Text. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing. Conference on Empirical Methods in Natural Language Processing*; 2022; Vol. 2022, p 3876.
37. Gong, H.; Chen, G.; Liu, S.; Yu, Y.; Li, G. Cross-Modal Self-Attention with Multi-Task Pre-Training for Medical Visual Question Answering. In *Proceedings of the 2021 international conference on multimedia retrieval*; 2021; pp 456–460.

UBC POLICY ACADEMIC INTEGRITY

The academic enterprise is founded on honesty, civility, and integrity. As members of this enterprise, all students are expected to know, understand, and follow the codes of conduct regarding academic integrity. At the most basic level, this means submitting only original work done by you and acknowledging all sources of information or ideas and attributing them to others as required. This also means you should not cheat, copy, or mislead others about what is your work. Violations of academic integrity (i.e., misconduct) lead to the breakdown of the academic enterprise, and therefore serious consequences arise and harsh sanctions are imposed. For example, incidences of plagiarism or cheating may result in a mark of zero on the assignment or exam and more serious consequences may apply if the matter is referred to the President's Advisory Committee on Student Discipline. Careful records are kept in order to monitor and prevent recurrences.
For more information, see: https://www.calendar.ubc.ca/vancouver/index.cfm?tree=3,286,0,0

USE OF GENERATIVE AI TOOLS

At the School of Biomedical Engineering, we believe that academic integrity is core to our educational mission, and are committed to upholding these values and skills. This is in line with UBC's stance on academic integrity, which you can learn more about here. As part of our educational mission, SBME is also committed to equipping our students with the competencies and tools needed to address complex and evolving challenges.

As Generative Artificial Intelligence (GenAI) technologies become more developed, it is crucial that you understand both the capabilities and limitations of these tools, so that – like any tool or technology – you may use them in a responsible and ethical manner. You are encouraged to review UBC's principles for the use of GenAI tools. The following was adapted from draft principles and guidelines prepared by UBC's Generative AI in Teaching and Learning Advisory Committee.

Key ethical considerations that you should be aware of as a learner:

- GenAI can be used in a way to support inclusion and accessibility
- GenAI outputs reflect social and cultural biases, which can reproduce systemic inequities, causing harm to individuals and communities
- GenAI outputs may be false, and therefore require critical evaluation by the user. This is also important to be aware of when GenAI tools are used for studying purposes.
- Different individuals have different levels of access to GenAI tools

As a student in UBC's SBME, you should always be submitting your own academic work, and using GenAI only when the course instructor provides you with clear permission to do so. Note that you should never submit resources created by TAs and instructors into GenAI tools without their express permission; this may constitute copyright infringement.

In cases where GenAI is permitted by your course instructor:

- Follow your instructor's guidance on how you may use GenAI in your academic work. Always clarify with your instructor if you have any questions.
- Critically reflect upon GenAI outputs through analysis, evaluation, and critique. This is also important in cases where GenAI is used for studying purposes (ie. chatbot as a tutor); be aware that GenAI outputs may not be reliable or accurate.
- Acknowledge your use of GenAI tools. You may refer to the UBC Library's Guide on Generative AI for more information.
- Your course instructor may request that you keep a record of prompts and outputs. In some cases, you may be asked to submit this record together with your academic work.

ACADEMIC CONCESSION

The University is committed to supporting students in their academic pursuits. Students may request academic concession in circumstances that may adversely affect their attendance or performance in a course or program. Students who intend to, or who as a result of circumstance must, request academic concession must notify their instructor, dean, or director as specified in the link below. https://www.calendar.ubc.ca/vancouver/index.cfm?tree=3,329,0,0

Students seeking academic concession due to absence from the final exam for any reason must apply to Engineering Academic Services (EAS) within 72 hours of the missed exam. This is a standard practice for all final examinations at UBC.

For more information, see: https://academicservices.engineering.ubc.ca/exams-grades/academic-concession/

STATEMENT ON UNIVERSITY'S VALUES AND POLICIES

UBC provides resources to support student learning and to maintain healthy lifestyles but recognizes that sometimes crises arise and so there are additional resources to access including those for survivors of sexual violence. UBC values respect for the person and ideas of all members of the academic community. Harassment and discrimination are not tolerated nor is suppression of academic freedom. UBC provides appropriate accommodation for students with disabilities and for religious observances. UBC values academic honesty and students are expected to acknowledge the ideas generated by others and to uphold the highest academic standards in all of their actions. Details of the policies and how to access support are available on the UBC Senate website.

LAND ACKNOWLEDGMENT

This course is held on the UBC Point Grey (Vancouver) campus, which sits on the traditional, ancestral, unceded territory of the xʷməθkʷəy̓əm (Musqueam) First Nation.