Form AR 140

The Hong Kong Polytechnic University

Subject Description Form

Subject Code	CMS6003
Subject Title	Learning Theory for AI
Credit Value	3
Level	6
Pre-requisite/ Co-requisite/ Exclusion	Expected to have undergraduate introductory background in - Probability and statistics - Linear algebra and calculus
Objectives	a. To provide students with in-depth knowledge on the key concepts in learning theory. b. To introduce the ability to theoretically analyse a learning algorithm's strengths and weaknesses. c. To enable students to understand how to modify existing models to suit different purposes and design new ones based on statistical principles.
Intended Learning Outcomes	Upon completion of the subject, students will be able to: a. Grasp the core mathematical and statistical principles behind learning algorithms. b. Analyse the generalization performance of machine learning algorithms. c. Appreciate the nature of the statistical foundations of designing or adapting learning algorithms. d. Understand most learning theory components in machine learning research papers.
Subject Synopsis/ Indicative Syllabus	**Fundamentals:** Objective function, Hypothesis class, estimation error, approximation error, empirical risk minimization, regularization, Bias and variance, underfitting and overfitting, convex optimization, surrogate loss functions, algorithmic robustness, concentration inequalities. **Advanced topics:** PAC learning framework, hypothesis complexity, generalization error bounds, VC-dimension, Rademacher complexity, algorithmic stability, algorithmic hypothesis complexity, stochastic gradient descent/weight decay makes machine learning algorithms stable, deep learning theory.
Teaching/Learning Methodology	Lectures to introduce main concepts and methodologies, together with in-class questions/answers/discussions for easy understanding.

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Attendance is compulsory to understand the abstract concepts, participate in in-class activities, and engage in meaningful interaction with the subject lecturer.
Tutorials sessions offer the opportunity to review the lecture contents and reference materials and for Q&A.
Assignments will give students the opportunity to comprehensively understand the concepts and do practice.
Quiz helps students to develop a solid foundation of statistical learning theory.
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<tr><td>Assessment Methods in Alignment with Intended Learning Outcomes
(Note 4)</td><td>
<table>
<tr><td rowspan="2">Specific assessment methods/tasks</td><td rowspan="2">% weighting</td><td colspan="4">Intended subject learning outcomes to be assessed (Please tick as appropriate)</td></tr>
<tr><td>a</td><td>b</td><td>c</td><td>d</td></tr>
<tr><td>1. Attendance / In-class activities</td><td>10%</td><td>√</td><td>√</td><td>√</td><td>√</td></tr>
<tr><td>2. Individual Assignments</td><td>30%</td><td>√</td><td>√</td><td>√</td><td>√</td></tr>
<tr><td>3. Quiz</td><td>30%</td><td>√</td><td>√</td><td></td><td></td></tr>
<tr><td>4. Group Assignments</td><td>30%</td><td>√</td><td>√</td><td>√</td><td>√</td></tr>
<tr><td>Total</td><td>100 %</td><td colspan="4"></td></tr>
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Explanation of the appropriateness of the assessment methods in assessing the intended learning outcomes:
In-class activities: In-class activities are as an informal assessment method, to facilitate interaction with students and to gauge their understanding of abstract concepts.
Assignment: evaluate the ability to understand and master the concepts, assess the independent learning and critical thinking abilities, written and peer communication skills.
Quiz: assessment of the overall performance by quiz or exam.
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<tr><td rowspan="5">Student Study Effort Expected</td><td>
<table>
<tr><td>Class contact:</td><td></td></tr>
<tr><td>▪ Lecture/Tutorial</td><td>30 Hrs.</td></tr>
<tr><td>Other student study effort:</td><td></td></tr>
<tr><td>▪ Self-study</td><td>50 Hrs.</td></tr>
<tr><td>▪ Assignments, Quiz</td><td>40 Hrs.</td></tr>
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	Total student study effort	120 Hrs.
Reading List and References	Boyd, S. P., & Vandenberghe, L. (2004). *Convex optimization*. Cambridge university press. Bartlett, P. L., Jordan, M. I., & McAuliffe, J. D. (2006). Convexity, classification, and risk bounds. *Journal of the American Statistical Association*, *101*(473), 138-156. Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2018). *Foundations of machine learning*. MIT press. Bousquet, O., Boucheron, S., & Lugosi, G. (2003). Introduction to statistical learning theory. In *Summer school on machine learning* (pp. 169-207). Berlin, Heidelberg: Springer Berlin Heidelberg. Vapnik, V. (2013). *The nature of statistical learning theory*. Springer science & business media. Domingos, P. (2000, June). A unified bias-variance decomposition. In *Proceedings of 17th international conference on machine learning* (pp. 231-238). Morgan Kaufmann Stanford. Boucheron, S., Lugosi, G., & Bousquet, O. (2003). Concentration inequalities. In *Summer school on machine learning* (pp. 208-240). Berlin, Heidelberg: Springer Berlin Heidelberg. Bartlett, P. L., & Mendelson, S. (2002). Rademacher and gaussian complexities: Risk bounds and structural results. *Journal of machine learning research*, *3*(Nov), 463-482. Bousquet, O., & Elisseeff, A. (2000). Algorithmic stability and generalization performance. *Advances in neural information processing systems*, *13*. Liu, T., Lugosi, G., Neu, G., & Tao, D. (2017, July). Algorithmic stability and hypothesis complexity. In *International Conference on Machine Learning* (pp. 2159-2167). PMLR. Hardt, M., Recht, B., & Singer, Y. (2016, June). Train faster, generalize better: Stability of stochastic gradient descent. In *International conference on machine learning* (pp. 1225-1234). PMLR. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, *15*(1), 1929-1958. Zhang, C., Bengio, S., Hardt, M., Recht, B., & Vinyals, O. (2017, February). Understanding deep learning requires rethinking generalization. In *International Conference on Learning Representations*. Bartlett, P. L., Foster, D. J., & Telgarsky, M. J. (2017). Spectrally-normalized margin bounds for neural networks. *Advances in neural information processing systems*, *30*.	