Form AR 140

# The Hong Kong Polytechnic University

## Subject Description Form

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| **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<br>- Probability and statistics<br>- Linear algebra and calculus |
| **Objectives** | a. To provide students with in-depth knowledge on the key concepts in learning theory.<br>b. To introduce the ability to theoretically analyse a learning algorithm's strengths and weaknesses.<br>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:<br>a. Grasp the core mathematical and statistical principles behind learning algorithms.<br>b. Analyse the generalization performance of machine learning algorithms.<br>c. Appreciate the nature of the statistical foundations of designing or adapting learning algorithms.<br>d. Understand most learning theory components in machine learning research papers. |
| **Subject Synopsis/ Indicative Syllabus** | **Fundamentals:**<br>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.<br><br>**Advanced topics:**<br>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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<tr><td></td><td>Attendance is compulsory to understand the abstract concepts, participate in in-class activities, and engage in meaningful interaction with the subject lecturer.<br><br>Tutorials sessions offer the opportunity to review the lecture contents and reference materials and for Q&A.<br><br>Assignments will give students the opportunity to comprehensively understand the concepts and do practice.<br><br>Quiz helps students to develop a solid foundation of statistical learning theory.</td></tr>
<tr><td>Assessment Methods in Alignment with Intended Learning Outcomes<br><br>(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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<br>Explanation of the appropriateness of the assessment methods in assessing the intended learning outcomes:<br><br>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.<br><br>Assignment: evaluate the ability to understand and master the concepts, assess the independent learning and critical thinking abilities, written and peer communication skills.<br><br>Quiz: assessment of the overall performance by quiz or exam.</td></tr>
<tr><td>Student Study Effort Expected</td><td>
<table>
<tr><td>Class contact:</td><td></td></tr>
<tr><td>▪ Lecture/Tutorial</td><td>39 Hrs.</td></tr>
<tr><td>Other student study effort:</td><td></td></tr>
<tr><td>▪ Self-study</td><td>43 Hrs.</td></tr>
<tr><td>▪ Assignments, Quiz</td><td>40 Hrs.</td></tr>
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| | Total student study effort | 122 Hrs. |
| **Reading List and References** | Boyd, S. P., & Vandenberghe, L. (2004). *Convex optimization*. Cambridge university press.<br><br>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.<br><br>Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2018). *Foundations of machine learning*. MIT press.<br><br>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.<br><br>Vapnik, V. (2013). *The nature of statistical learning theory*. Springer science & business media.<br><br>Domingos, P. (2000, June). A unified bias-variance decomposition. In *Proceedings of 17th international conference on machine learning* (pp. 231-238). Morgan Kaufmann Stanford.<br><br>Boucheron, S., Lugosi, G., & Bousquet, O. (2003). Concentration inequalities. In *Summer school on machine learning* (pp. 208-240). Berlin, Heidelberg: Springer Berlin Heidelberg.<br><br>Bartlett, P. L., & Mendelson, S. (2002). Rademacher and gaussian complexities: Risk bounds and structural results. *Journal of machine learning research*, *3*(Nov), 463-482.<br><br>Bousquet, O., & Elisseeff, A. (2000). Algorithmic stability and generalization performance. *Advances in neural information processing systems*, *13*.<br><br>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.<br><br>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.<br><br>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.<br><br>Zhang, C., Bengio, S., Hardt, M., Recht, B., & Vinyals, O. (2017, February). Understanding deep learning requires rethinking generalization. In *International Conference on Learning Representations*.<br><br>Bartlett, P. L., Foster, D. J., & Telgarsky, M. J. (2017). Spectrally-normalized margin bounds for neural networks. *Advances in neural information processing systems*, *30*. | |