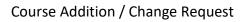
Office of the Registrar





New Courses			
Program:			
COURSE NUMBER:	COURSE TITLE: Mathematical Introduc	ction to Deep Learning (CREDITS:
Contemporary Topics Course	e:		
aspects of deep learning techniqu analyze and to further develop r students who want to learn abo	tached syllabus) This is a course on the intesting the syllabus. This is a course on the intesting the syllab syll	al background and also practical to applications. The course is simul- ing and also towards students fro	ools needed to understand, to taneously geared towards math om other fields who are
Pre-requisites: linear algebra, r	multivariable calculus Co-requisites:	Core Requirement:	YES NO
* Use additional pages if necessary			
Existing Courses			
PROGRAM:	COURSE NUMBER*:	COURSE TITLE <u>Deep learn</u>	ing Algorithms and Analysis
Proposed Changes(use additional	pages if necessary):		
*Course number cannot be reassigned	d unless the course has been dormant for three y	<i>y</i> ears	
Signature of Program Chair:		Date:	(mm/dd/year)
Signature of Division Dean:		Date:	(mm/dd/year)
Curriculum Committee Approval	YES NO	Date:(mm/d	ld/year)
Program notified:	(mm/dd/yy) Added to Curriculum:	(mm/dd/yy)	
Processed By:	Signature:	Date:	



*Required

Course addition - Syllabus: Course Title*			
Division*:	CEMSE		
Course Number:	AMCS ****		
Course Title (Limited to 40 characters)*:	Deep Learning and Analysis		
Expected Starting Academic Semester*:	Spring 2023		
Expected Starting Academic Year*:	2023		
Course proposer(s)*:			
Name(s) *:	Jinchao Xu		
Phone:			
Email*:	jinchao.xu@kaust.edu.sa		
Instructor(s) information			
Name(s) *:	Jinchao Xu		
Phone:			
Email*:	jinchao.xu@kaust.edu.sa		
Prerequisite Course Number*:	Linear algebra; multivariable calculus		
Comprehensive Course Description*:	This is a graduate course on the introduction of basic mathematical, numerical and practical aspects of deep learning techniques. It will provide students with the mathematical background and also practical tools needed to understand, analyze and further develop numerical methods for deep learning methods and applications. The course is simultaneously geared towards math students who want to learn about the emerging technology of deep learning and also towards students from other fields who are interested in deep learning application but would like to strengthen their theoretical foundation and mathematical understanding.		
Course Description for Program Guide*:	Prerequisites: linear algebra and multivariable calculus. Familiarity with machine learning or artificial intelligence recommended. Topics: linear regression, SGD, learning theory, finite element, DNNs, approximation theory, CNNs, multigrid methods, and MgNet.		
Goals and Objectives*:	 Understand basic ideas of machine learning and why deep learning works. Learn to implement deep learning algorithms using Python and PyTorch. Application of deep learning for image classifications. 		
Required Knowledge*:	Linear algebra; multi-variable calculus; some programming experiences with Python are helpful.		
Reference Texts*:	 Goodfellow I., Bengio Y. and Courville A. Deep learning. MIT press, 2016. Xu J. Deep Learning and Analysis, Lecture Notes (to be published by Springer). 		

40% - Homework
20% - Midterm exam
20% - Final exam
20% - Final project
Homework consist of written homework for conceptual questions and programing assignments for practical exercises. The final homework score will be the average taking on all assigned homework. The final project will be closely related to topics in this course.
Please pay attention to the due date of the assignments. No late homework will be accepted. Attendance is mandatory. Students should notify the instructor in advance of missing any class or as soon as possible thereafter.

NOTE

The instructor reserves the right to make changes to this syllabus as necessary.

Tentative Course Schedule: (Time, topic/emphasis & resources)		
Week/Lecture	Topic	
1	Introduction; logistic regression	
2	Multivariable calculus, convexity, gradient descent method	
3	Elements of probability; stochastic gradient descent.	
4	Elements of machine learning theory;	
5	Python, implementation and MNIST	
6	Introduction to linear finite element space	
7	Shallow neural network (NN) functions and approximation theory	
8	Implementation: shallow NN for MNIST	
9	Deep neural networks; convolutional neural networks	

10	Initialization; batch normalization; implementation: CNN for MNIST
11	The Poisson equation and linear finite element method
12	Gradient descent and smoothing properties; multigrid method
13	MgNet: from multigrid to a special CNN
14	MgNet: Applications
15	Transformers and other neural networks; Review