CS 4602

Introduction to Machine Learning

NTHU / Autumn 2021-2022

Instructor: Po-Chih Kuo (郭柏志)

Human-Centered Machine Intelligence Lab
https://pochihkuo.github.io/

Logistics

- **Instructor:** Po-Chih Kuo (郭柏志)
  - Email: kuopc@cs.nthu.edu.tw
  - Office: Delta 630
  - Office hours: Wednesdays 14:30-15:30


Po-Chih Kuo
郭柏志

- **TA:**
  - TA hours: Thursday 17:00-18:00
  - Make a reservation via google doc by Thursday 10am

https://docs.google.com/spreadsheets/d/1aotMMgXQlMGPoycSLi_0rTm-KzJc_heHIozsOTpR0Jw/edit#gid=0


Meng-Chien Lin
林孟謙


Yi-Shiuan Tseng
曾怡瑄


Ivan Lim
林家合


Po-Chun Lin
林柏均


Li-Ching Chen
陳立晴


Ryan Wang
王瑞恩

Communication

- We will use eLearn for all communications: announcements and questions related to lectures, assignments, and projects.
  - You should be added to the eLearn automatically
- Teams will be used for remote lecture

Prerequisites

- This course covers a lot of ground
  - Calculus
  - Probability
  - Programming: Python

Rules

- Remote lecture
- English is the official language (some mandarin)
- No roll call but there might be bonus for attendance
- Ask and answer questions! (Mandarin is acceptable)
- It will be awesome if you can turn on y camera

~~Textbook~~

- There is no required textbook for this class
- You should be able to learn everything from the lecture slides and homework
- Lecture slides will be uploaded to eLearn

References

- “Pattern Recognition and Machine Learning”
- Christopher Bishop
- ISBN: 978-0387310732

- “Deep Learning”
- Ian Goodfellow, Yoshua Bengio, and Aaron Courville
- ISBN: 978-0262035613

- “Introduction to Machine Learning with Python”
- Andreas C. Müller, Sarah Guido
- ISBN: 978-1449369415

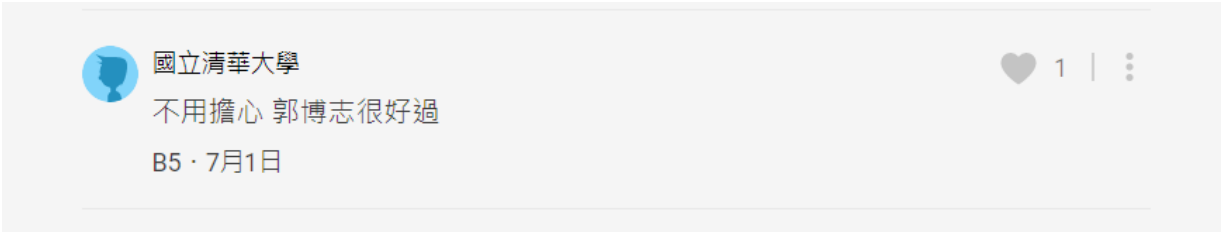
- “An Introduction to Machine Learning”
- Miroslav Kubat
- ISBN: 978-3319200101
- (Electronic version is available from the library)

Goals

- To understand the basic principles of machine learning
- To become familiar with widely used machine learning algorithms
- To learn how to use machine learning algorithms to solve real problems
- To properly evaluate the model performance
- Little math

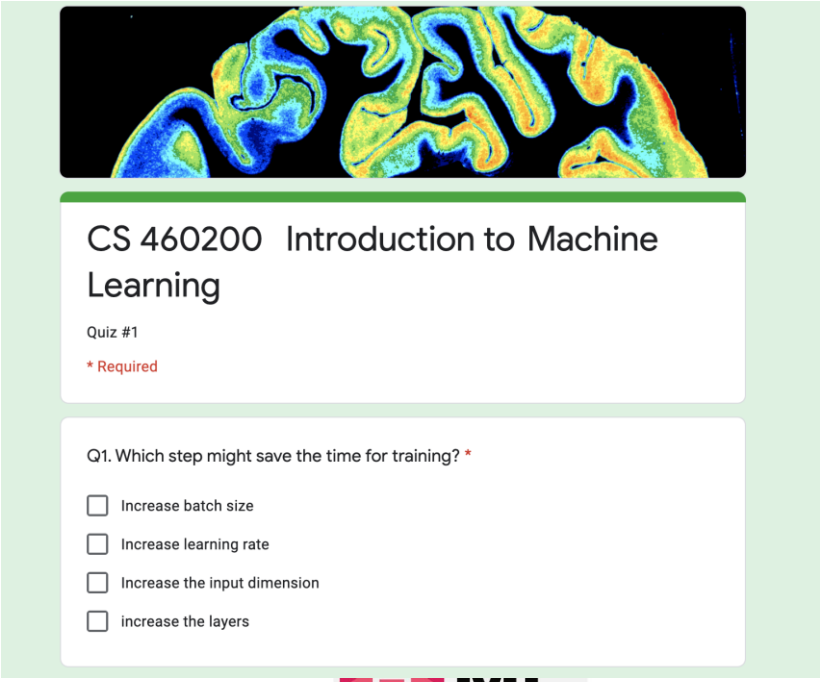
Evaluation

- Exams: 30%
- Assignments: 40%
- Term project: 30%



Evaluation (Cont.)

- 4 Exams: 30%
  - Answer by your smartphone or laptop



Evaluation (Cont.)

- 5 assignments: 40%
  - Due two weeks after the announcement
  - Google Colab is recommende 
  - The scores will be given based on your model's performance on testing data, which are held in our hands (35%).
  - Hand in a brief report (5%)
  - Do not plagiarism

Evaluation (Cont.)

- Term project: 30%
  - Any ML-related projects are welcome
  - 3-6 members per team (Teamwork is recommended!)
  - Hand in your proposal during mid-term (10%)
    - 5 % from TAs and 5% from Lecturer.
    - Give a brief presentation in English on your project
      - 3 mins for each team by video.
      - Introduce your topics and team members “with Photo”.
    - 10 top-ranked team will got extra 1 point to the total grade.

Evaluation (Cont.)

- Final presentation (in English, 5 mins presentation + 3 min QA) at the end of the semester
- Hand in a report (2-8 pages) with the format as an IEEE paper including Introduction, Methods, Results and Conclusions
- Evaluated by TAs and instructor (20%)

2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)
April 3-7, 2020, Iowa City, Iowa, USA

LOOKING IN THE RIGHT PLACE FOR ANOMALIES: EXPLAINABLE AI THROUGH AUTOMATIC LOCATION LEARNING

Satyananda Kashyap, Alexandros Karargyris, Joy Wu, Yaniv Gur, Arjun Sharma
Kim C. L. Wong, Mehdi Moradi, Tanveer Syeda-Mahmood

IBM Research Almaden

ABSTRACT

Deep learning has now become the de facto approach to the recognition of anomalies in medical imaging. Their 'black box' way of classifying medical images into anomaly labels poses problems for their acceptance, particularly with clinicians. Current explainable AI methods offer justifications through visualizations such as heat maps but cannot guarantee that the network is focusing on the relevant image region fully containing the anomaly. In this paper we develop an approach to explainable AI in which the anomaly is assured to be overlapping the expected location when present. This is made possible by automatically extracting location-specific labels from textual reports and learning the association of expected locations to labels using a hybrid combination of Bi-Directional Long Short-Term Memory Recurrent Neural Networks (Bi-LSTM) and DenseNet-121. Use of this expected location to bias the subsequent attention-guided inference network based on ResNet101 results in the isolation of the anomaly at the expected location when present. The method is evaluated on a large chest X-ray dataset.

1. INTRODUCTION

Deep learning is now the dominant paradigm in AI. Despite the large number of layers now being used, the networks are optimized based on a single objective function through basic mechanisms of back propagation. As a result, it has become increasingly difficult to explain if the network output is driven by the relevant image region. This particularly poses a problem in radiology reads, where the clinicians not only need to be convinced that the machine is classifying correctly, but that it is driven by features within the relevant region containing the anomaly [1]. Unlike rule-based expert systems or decision tree methods which can externalize the feature choices, deep neural networks do not automatically provide explainable features. Current explainable AI methods focus on post-explanations by either generating visual explanations such as layer-wise relevance propagation [2] and heat maps, transforming the labels to show higher level semantic associations [3] or rationalizing neural predictions by identifying relevant regions in text [5]. The relevancy of regions is also built into the object detection formalisms in computer vision where current networks such as RetinaNet solve for both the object category and its predicted image location [4]. These formalisms typically search for objects through bounding boxes in several locations, and orientations through single pass [5, 6] or two pass networks [7] that first propose candidate region and then classify the regions to match to both location and label for the object. However, none of these approaches can guarantee that the network is focusing in the relevant image region.

In this paper we develop an approach to explainable AI in which the anomaly is designed to be overlapping the expected location when present. This is made possible by automatically extracting location-specific labels from textual reports and learning the association of expected locations to labels using a Bi-Directional Long Short-Term Memory Recurrent Neural Networks (Bi-LSTM). Use of this expected location to bias the subsequent attention-guided inference network based on ResNet101 results in the isolation of the anomaly at the expected location when present. The method is evaluated on a large chest x-ray dataset. Comparison to direct image-based classification approaches shows an improvement in accuracy of classification while still ensuring that the anomaly is localized in its expected location, thus leading to a better justification for the learned model. Some of the large scale medical image collections are accompanied by radiology text reports. Mining these reports for possible location cues can generate location hints. This approach was used recently to annotate for anomalies in earlier work [8]. In [8], MESH terms extracted from text paragraphs were used in an LSTM formulation to predict the location. However, not all terms in the text may be relevant for the localization. While the unidirectional LSTM formulation can model the sequence order in dictated reports, due to the variations in which anomalies and their locations are described, missing and spurious terms can occur requiring the use of bi-directional models. Finally, the end point of the localization approaches is the regression of the location coordinates whereas the problem addressed in this paper is the classification of the anomalies taking the expected location into account for improved accuracy. The main contributions of the paper are as follows:

1. Automated inference of findings and their locations from

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Syllabus

- Introduction and Basic Concepts
- Regression
- Bayesian Classifiers
- Decision Trees
- KNN
- Linear Classifier
- Neural Networks
- Deep learning
  - Convolutional Neural Networks
  - Autoencoder
  - Adversarial
  - RNN
- Reinforcement Learning
- Model Selection and Evaluation
- Clustering
- Dimensionality reduction

Error-Based Learning

Probability-Based Learning

Information-Based Learning

Similarity-Based Learning

Unsupervised Learning

September 2021

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
			1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21 ●	22	23	24	25
26	27	28 ●	29	30 ▲		

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Introduction and Basic Concepts

Regression

October 2021

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31						

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Bayesian Classifiers

Decision Trees

Linear Classifier

Neural Networks

November 2021

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
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21	22	23	24	25 ♥	26	27
28	29	30 ⚡				

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Deep learning

Convolutional Neural Networks

Autoencoder

Adversarial

RNN (Transformer)

December 2021

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
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12	13	14	15	16	17	18
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26	27	28 ⚡	29	30	31	

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Reinforcement learning

Model Selection & Evaluation

Clustering

Dim. Reduction

Recap

JANUARY 2022

SUN	MON	TUE	WED	THU	FRI	SAT
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9	10	11 ♥	12	13 ♥	14	15
16	17	18	19	20	21	22
23	24	25	26	27	28	29
30	31					

Printable Calendars From **123Calendars.Com**

⚡ Quiz

▲ Assignment

● Holiday

♥ Upload proposal presentation

♥ Project presentation

☁ Human-Centered Machine Intelligence in Healthcare (HMIH) Workshop

Human-Centered Machine Intelligence in Healthcare (HMIH) Workshop

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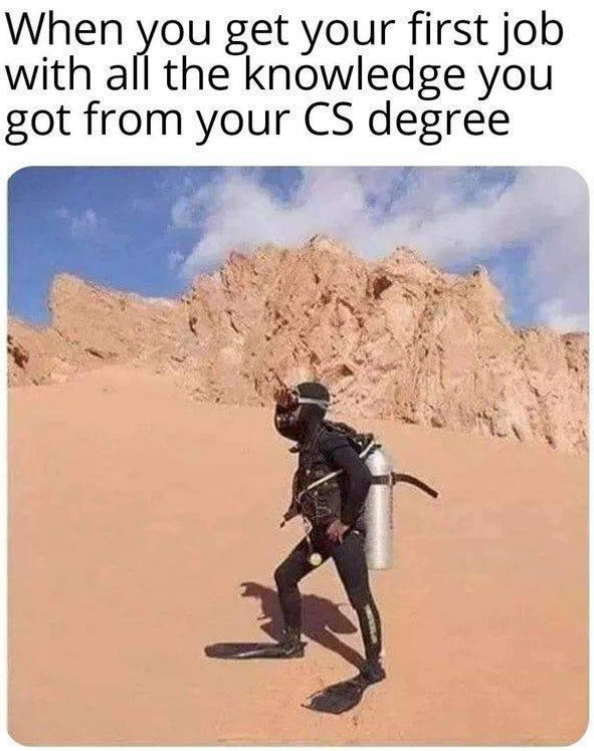
Quiz time!

Questions?


When you get your first job with all the knowledge you got from your CS degree