# 期末報告事項

2023

Machine Learning and Deep Learning

# 評分

- ·期中考-30%(選擇題20題)
- ·期末報告-60% (二選一): 5/2繳交名單
  - Python程式實作機器學習或深度學習 (不分組,每位修課同學均要 繳交期末報告與程式碼)
    - 題目可自選
  - · 直接參與Kaggle競賽(題目可於kaggle上自選,或使用指定題,仍要 繳交期末報告與程式碼)(可組團,1~3人)
- 課堂表現 10%

Тор	0-20%	21 – 30%	31 – 40%	41 – 50%	51% - 60%	61-70%	71% -
成績	100	95	90	80	70	60	0

因kaggle上的成績會變動,請上傳成績最好的top%截圖

+

學號與姓名。	題目。	是否為 kaggle 比賽。		
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# 報告繳交

- •報告繳交日期: 2021年6月13 (期末考週)•
- ·繳交方式:上傳ftp server
- •研究報告包括二個
  - 報告: pdf格式儲存, 第一頁為學號, 姓名及題目, 檔名為: 學號.pdf
  - •程式: 檔名為: 學號.ipynb
  - · 若為kaggle比賽,則在報告上附上比賽成績

# 期末報告 60%

# 資料集下載

- Kaggle
  - https://www.kaggle.com/
- 政府開放資料平台
  - http://data.gov.tw/
- • 美國開放資料平台
  - https://www.data.gov/
- • 加州大學爾灣分校機器學習資料
  - http://archive.ics.uci.edu/ml/
- Stanford Large Network Dataset Collection
  - https://snap.stanford.edu/data/
- Google Dataset Search
  - https://toolbox.google.com/datasetsearch

# Google Dataset Search

# 期末報告 60%

# 期末報告 格式

## 調查:在課堂中使用GitHub能大幅提升學生進入業界自信

2018 Classroom Report



- 摘要
- 介紹(研究背景及研究目的)
- 資料集介紹(含資料特徵)及資料集來源
- 資料預處理
- 機器學習或深度學習方法 (使用何種方法)
- 研究結果及討論(含模型評估與改善)
- 結論
- 參考文獻

# 期末報告

# 格式範例

# Sample

## Stanford

## Earthquake warning system: Detecting earthquake precursor signals using deep neural networks

SCHOOL OF EARTH, ENERGY & ENVIRONMENTAL SCIENCES

Mustafa Al Ibrahim, Jihoon Park, and Noah Athens {malibrah, jhpark3, nathens}@stanford.edu

### **ABSTRACT**

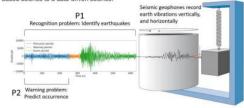
Earthquake prediction is one of the great unsolved problems in the earth sciences. In recent years, the number of seismic monitoring stations has increased, thereby enabling deep learning and other data-driven methods to be applied to this problem. In this study, we test the performance of 1D CNN, 2D CNN, and RNN neural networks on predicting an imminent earthquake given 100 seconds of seismic data. Preliminary results show that RNN with class weighting is preferred. We also show the performance of these methods on earthquake recognition, a simpler problem with applications to data mining earthquake statistics.

#### INTRODUCTION

"Journalists and the general public rush to any suggestion of earthquake prediction like hogs toward a full trough... [Prediction] provides a happy hunting ground for amateurs, cranks, and outright publicity-seeking fakers."

Charles Richter, 1977

Earthquake seismology is a major topic relevant to understanding hazards due to natural and induced earthquakes as well as understanding physical properties of the earth's crust. In the past decade, the number of seismic monitoring stations has increased dramatically, leading the field of research to transition from an observationbased science to a data-driven science.



### Two binary classification problems addressed:

#### (P1) Given a seismic waveform, has an earthquake occurred?

The earthquake recognition problem is useful for data mining massive volumes of seismic data in which smaller magnitude earthquakes may not have been previously detected. State of the art performance is high, ~87% accuracy is achievable [1].

#### (P2) Given a seismic waveform, will an earthquake occur?

The earthquake warning problem is important for developing a warning system that can alert people to an imminent earthquake. Although long-studied in the field of seismology, there is no proven analytical method to predict earthquakes before they occur [2].

#### The Geysers study area:

- · The area is seismically active
- · 46 seismometer stations.
- Single channel (vertical). · Decades of monitoring data.
- · An enhanced geothermal system program (EGS) began in 2009 and seismic data was recorded before and after water injection to study induced seismicity.



## **DATASET AND FEATURES**

We used the Obspy library [3] to assemble the dataset through the procedure outlined.

We experimented with differer datasets, determining that tightly clustered stations is preferred.

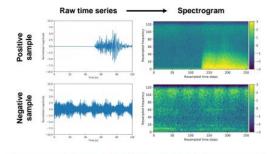
Three datasets are assembled with 1671, 614, and 176 earthquakes using a minimum magnitude (M) of 3, 3.5, and 4 respectively.

(A3) RNN on spectrogram data

Query server for Estimate the arrival time of the maximum of 10 km earthquake to the away from the station using the "iasp91" model

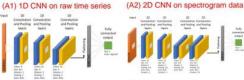
Retrieve Retrieve a earthquake signal randomly selected hased on estimated interval from the arrival time same station (positive sample) (negative sample)

Spectrogram (a representation of energy of the signal at different frequencies) is calculated and used as an input for the 2D CNN and the RNN network architectures.



#### DEEP LEARNING APPROACH

Multiple neural network architecture were tested starting with a simple 1D CNN on the raw time series data to an RNN on the spectrogram data



#### STUDY AREA

#### Hyperprameters explored include:

- Number of layers
- Filter and pooling size CNN only Number of epochs (ep)
- Learning rate (Ir)
- Class weights (cw)
- Dropout rate Dilation rate - CNN only
- Spectrogram upscaling size
- Number of units RNN only

### **RESULTS & DISCUSSION**

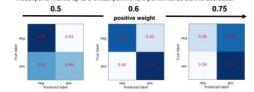
#### (P1) Earthquake recognition:

Model	Parameters	Training Accuracy	Test Accuracy
D CNN	M = 3.5, lr = 0.001, ep = 10	97.5%	94.4%
D CNN	M = 3.5, Ir = 0.001, ep = 10	100%	100%
NN	M = 3.5, Ir = 0.001, ep = 50	100%	100%

#### (P2) Earthquake prediction:

Model	Parameters	Accuracy	Test Accuracy
1D CNN	M = 3, ir = 0.002, ep = 40	56.0%	54.2%
2D CNN	M = 3, ir = 0.001, ep = 12	60.0%	52.6%
	M = 3, Ir = 0.001, ep = 100, cw = [0.5, 0.5]	82.5%	54.5%
RNN	M = 3, ir = 0.001, ep = 100, cw = [0.4, 0.6]	83.8%	56.4%
	M = 3, Ir = 0.001, ep = 100, cw = [0.25, 0.75]	74.7%	53.9%

- · Our results demonstrate high performance on the earthquake recognition problem (P1) but low performance on the prediction problem (P2).
- · 2D CNN and RNN models both performed better than the 1D CNN model. This is expected as the spectrogram is a more convenient representation of the data and information contained in the signal.
- · Preliminary results suggest that slightly penalizing false positives might improve model performance up to a critical point where performance start to decrease.



### CONCLUSIONS

- · All of the presented neural network models achieved high performance on the earthquake recognition problem (P1).
- · Predicting earthquakes before they occur (P2) is still a challenging problem. Based on the current analysis, some seismic precursor signal may exist.

### **FUTURE WORK**

- · Experiment with cleaner and bigger datasets.
- · Study the neural layers that activate for the true positive cases in the prediction
- · Explore the relationship between warning time and prediction accuracy.

#### REFERENCES

- 1. Yoon, C.E., O'Reilly, O., Bergen, K.J., and Beroza, G.C., 2015, Earthquake detection through computationally efficient
- 2. Geller, R.J., Jackson, D.D., Kagan, Y.Y., and Mulargia, F., 1997, Earthquakes cannot be predicted: Science, vol. 275, 1 p.
- 3. Krischer, L., Megies, T., Barsch, R., Beyreuther, M., Lecocq, T., Caudron, C., Wassermann, J., 2015, ObsPy: a bridge for seismology into the scientific Python ecosystem: Computational Science & Discovery

# 期末報告 60%

# 期末報告格式範例

# Sample



# \*\*CeafNet: A Deep Learning Solution to Tree Species Identification

OUTPUT

Label

APPLICATIONS

Species

conservation

Educational

Purposes

Precision vs. Epoch

Elena Galbally, Krishna Rao, and Zoe Pacalin CS230 Deep Learning, Stanford University

**Model and Results** 

MODEL

Resnet18 +

Parameters

(see table)

### Abstract

Species identification of vegetation is a key step in plant biodiversity research and conservation biology. Speeding up this process can boost humanity's ability to mitigate climate change impacts by simplifying species conservation efforts and helping educate the public. In this study we used a Residual Network to classify 185 tree species from North America using leaf images.

## **Dataset and Features**

### LeafSnap dataset:

- 224x224 RGB images
- 185 species
- 23,147 lab images (top)
- 7719 phone images (bottom)

#### Modifications:

- Geolocation labelling: assign random coordinate pair within the growing region of a species.
- Data augmentation through rotations









## Performance Criteria

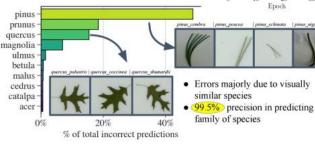
INPUT

RGB Image

Optimizing metric: maximize top-1 precision Satisficing metric: model < 100 Mb

## System performance:

 Beats the highest performing system on the LeafSnap dataset by 7.5%



## Conclusions

The results of our ResNet model show deep learning offers a high precision and throughput solution for leaf species classification.

Compared to state-of-art methods our system:

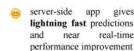
- Has the best precision
- · Uses a relatively small number of layers
- Requires less epochs to converge

Novelties of the approach:

- Deployed on a phone app
- Geolocation input feature
- · SGD optimizer w/ Nesterov momentum
- Fewer layers

## Try it now!

- Open Hangouts with leafnetstanford@gmail.com
- · Say "Hi bot" and start using!









Acknowledgements: CS230 teaching staff, leafsnap.com, Dr. Joseph Berry, Dr. Leander Anderegg

# Kaggle競賽

# •三選一

- 波士頓房價預測
  - https://www.kaggle.com/c/house-prices-advanced-regressiontechniques
- 鐵達尼號生存預測
  - https://www.kaggle.com/c/titanic
- 自選Competition on Kaggle



Kaggle是一個數據建模和數據分析競賽平台。企業和研究者可在其上發布 數據,統計學者和數據挖掘專家可在其上進行競賽以產生最好的模型。這 一眾包模式依賴於這一事實,即有眾多策略可以用於解決幾乎所有預測建 模的問題,而研究者不可能在一開始就了解什麼方法對於特定問題是最為 有效的。 維基百科

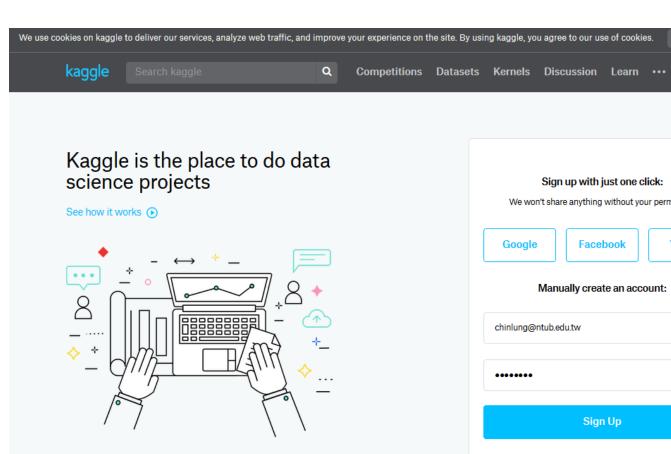
創辦人: 安東尼 戈德布盧姆

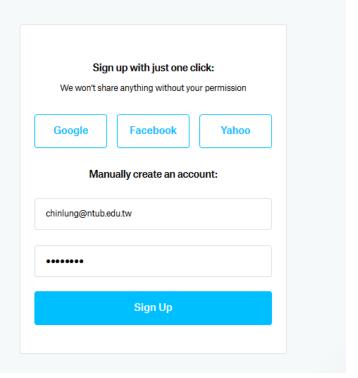
創立於: 2010年4月

**執行長:** 安東尼·戈德布盧姆 (2010 年 4 月-)

總部: 美國加利福尼亞州舊金山

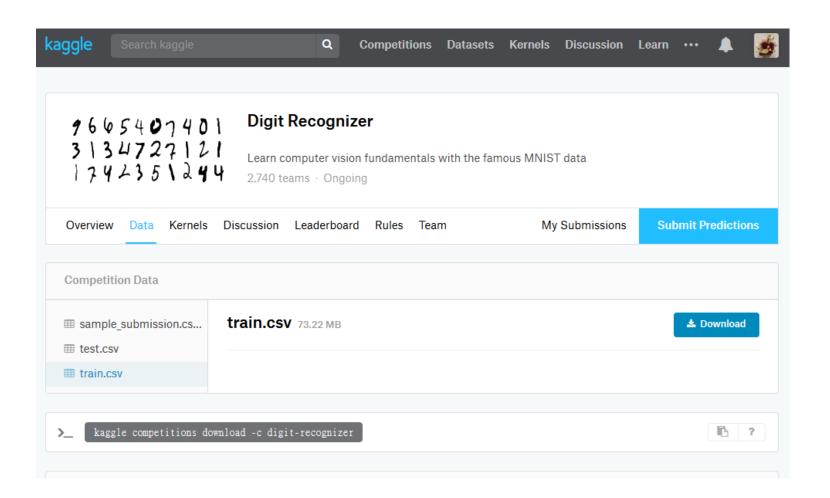
上級機構: Google

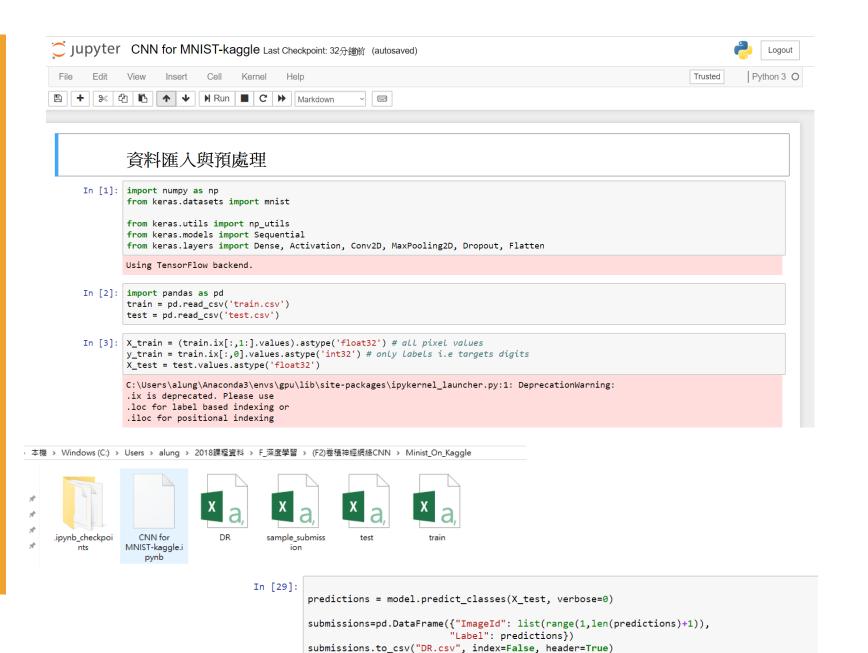


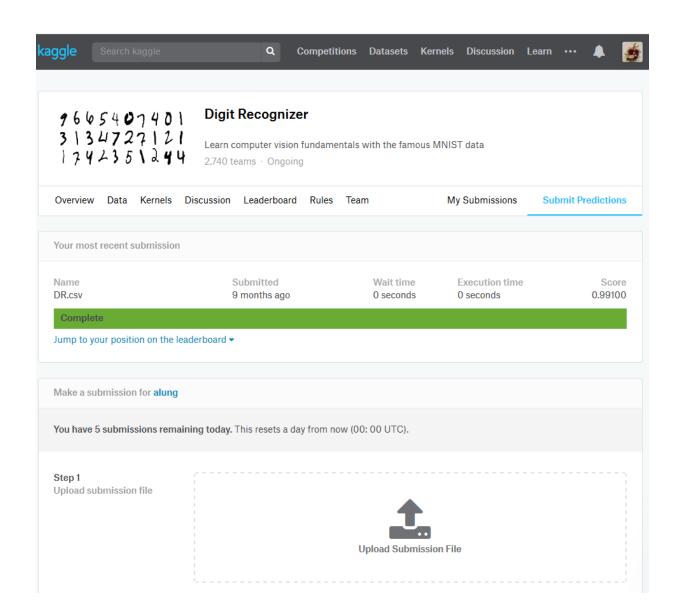


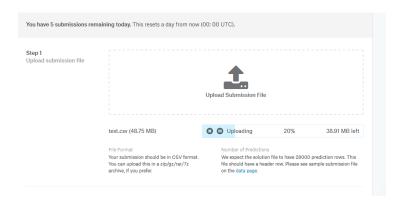
Learn more

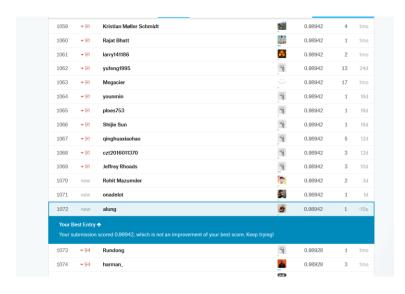
Got it

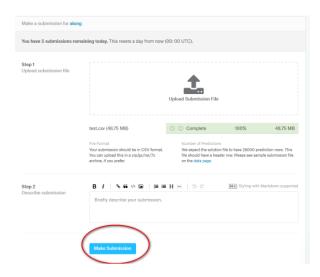


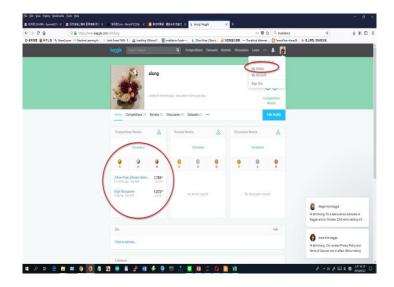




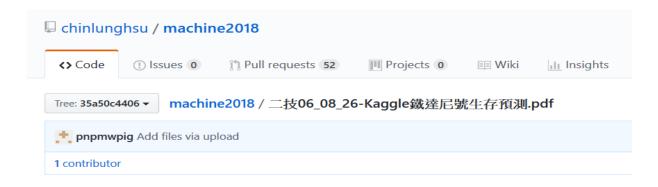




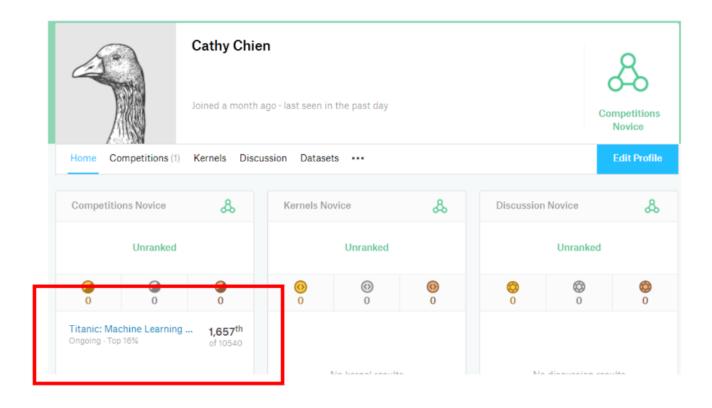




# 教學成果o1



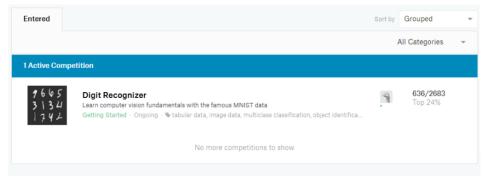
# Kaggle 排名如下圖



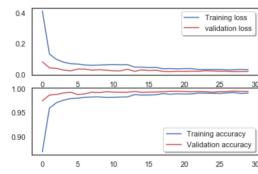
# 教學成果o2

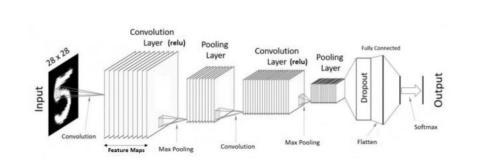
# Result

- Competition Ranking
  - 636/2683 Top 24%

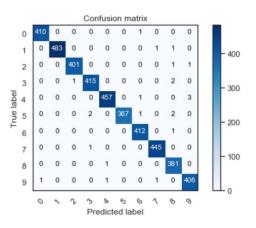


# Train/Validation lost and accuracy





## Confusion matrix



# 教學成果o3

CHANGED 2 MONTHS AGO

## 摘要

在一學期的機器學習與深度學習課程後,於Kaggle平台上選定一資料集進行分析。

## 介紹

## 研究目的

本次選定 Black Friday 這個資料集,Black Friday 在美國用來指每年感恩節之後的第一天。這一天 通常被認為標誌著聖誕購物期的正式開始,被看作是每年零售業聖誕銷售業績的晴雨表,也是一 年中各個商家最看重也是最繁忙的日子之一。中文又稱作黑色購物節。

本次期室由 Kaggle上 的 dataset 進行機器學習與深度學習練習,並選定一種方法進行預測與建議。

The dataset here is a sample of the transactions made in a retail store. The store wants to know better the customer purchase behaviour against different products. Specifically, here the problem is a regression problem where we are trying to predict the dependent variable (the amount of purchase) with the help of the information contained in the other variables.

----截自Black Friday中的Description

## 研究目標

- 分析資訊
- 主要客群為男或女、結婚與否
- 回歸與分類,並預測
- 試用回歸法預測購買量
- 〇 試用分類法預測是否為較高消費群

摘要 介紹 實作解析 研究結果與討論 結論 參考文獻 Expand all

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```
def show_train_history(train_history,train,validation):
   plt.plot(train_history.history[train])
   plt.plot(train_history.history[validation])

4   plt.title('Train History')
   plt.ylabel(train)
   plt.xlabel('Epoch')
   plt.legend(['train', 'validation'], loc='upper left')
   plt.show()
   show_train_history(train_history,'acc','val_acc')
   show_train_history(train_history,'loss','val_loss')
```

