한국기술교육대학교 능력개발교육원 4차 산업혁명 핵심 기술 컨퍼런스 2020년 1월 21일

4차 산업혁명 인재양성을 위한 인공지능 (Al) 교수 방법 <sup>입성규</sup> (조지아 공대)





- 1. 인공지능 (AI) 기계학습이란?
- 2. 기계학습의 종류
  - CNN, RNN GAN, Autoencoder, Unet
- 3. 기계학습 교수법 및 코딩 실습의 예
  - RNN으로 주가 변동 예측하기
  - Azure로 붓꽃 판별하기
- 4. 기계학습 관련 진행 연구
  회로설계에 적용된 기계학습

### 인공지능 (AI) 국가전략



# 인공지능 (AI) 국가전략



# 제 2의 석유

- Who has the world's largest photo DB?
  - How do we make \$\$\$ out of this?
- Who has the world's largest video DB?
  - How do we make \$\$\$ out of this?
- Who has the world's largest shopping DB?
  - How do we make \$\$\$ out of this?
- Who has the world's personal DB?
  - How do we make \$\$\$ out of this?





### 글로벌 시가총액 5대 기업

	2007년	2017년
1위	페트로 차이나	애플
2위	엑손 모빌	구글
3위	제너럴 일렉트릭	마이크로 소프트
4위	차이나 모바일	아마존
5위	중국 공상 은행	페이스북

https://en.wikipedia.org/wiki/list\_of\_public\_corporations\_ by\_market\_capitalization

### 2019년 12월 30일 뉴스

### 日 GDP 급 시총 5조달러 테크기업 빅5, '70년 美 패권' 이어나가는 힘이다



### └ 인터넷→모바일→ 이젠 플랫폼으로 21세기도 움켜쥐는 美



# I. 인공지능 (AI) 기계학습이란?



### 딥러닝이란? [네이버 지식백과]

- 사물이나 데이터를 군집화하거나 분류하는 데 사용하는 기술
  - 컴퓨터는 사진만으로 개와 고양이를 구분하지 못함
  - 하지만 사람은 아주 쉽게 구분할 수 있음
  - 이를 위해 기계학습 (Machine Learning) 이라는 방법이 고안됨





### Human Brain

Amazing structure



### 천억개의 뉴런들이 백조개의 시냅스로 연결

### Sung Kyu Lim, Georgia Tech (2019)

### **Deep Neural Network**

- DNN simply has more hidden layers than ANN
  - More weights to tune
  - Becomes more powerful

### Simple Neural Network

Input Layer

Hidden Layer

Output Layer

Deep Learning Neural Network

### https://www.youtube.com/channel/ UCvX15F7CzUMqf8P7sHtWATA

# X deep learning mouse

### 딥러닝의 계보



Perceptron

McCulloch & Pitts math model



Hinton DNN, back propagation

# Rosenblatt computer simulation

# 인공지능/딥러닝 부활의 이유





14/96

### **ML** Doctor



### Al Human Resources In Great Need



Sung Kyu Lim, Georgia Tech (2019)

16/96

### 한국 AI 인재 구축의 문제점

- AI 인력을 확보하는 데 가장 큰 애로 요인
  - 실무형 기술인력 부족 (36,7%)
  - 선진국 수준의 연봉 지급이 어렵다 (25.5%)
  - 대학원 등 전문 교육기관 및 교수 부족 (22.2%)
  - 근로시간 등 경직된 근무환경 및 조직문화 (6.7%)
  - 예산지원, 규제 완화 등 정부 지원 부족 (6.7%)
- 국내 AI 인재 육성을 위해 가장 필요한 것
  - 교육 인프락 확대 (37.8%)
  - 기술혁신 및 신산업 창출을 저해하는 규제 완화'(21.1%)
  - AI 관련 스타트업 창업 및 기업의 AI 인재 육성 제도적 지원'(13.3%)
  - AI 인재 유치를 위한 근로환경 및 기업문화 조성'(12.2%)



# 2. 기계학습의 종류



CNN, RNN GAN, Autoencoder, Unet



# Convolutional Neural Network (CNN)



### Yann LeCun's Job @ Facebook







### Suggested Post, Banner Ads

### **Image Recognition**

• Crucial in many ML applications



### • Main challenge: # of pixels!!!!!!

### **Convolutional Neural Network (CNN)**

- What is Convolution?
  - 영상으로부터 특정 feature들을 추출하기 위한 필터를 구현할 때 convolution을 사용
- Why CNN?
  - Yann LeCun (1998)
  - 이미지 인식에서 MLP (Multi-Layer
     Perceptron)를 사용하게 되면, MLP는
     모든 입력이 위치와 상관없이 동일한
     수준의 중요도를 갖음
  - 이를 이용해 fully-connected neural network를 구성하게 되면 model 크기가 엄청나게 커지는 문제가 생김
  - 이에 대한 해결책으로 탄생한 것이 CNN





### **CNN Deep Learning**

- Feature Extraction
  - Key idea to manage complexity while maintaining accuracy
  - Features are extracted via CONV:RELU:POOL



### **CNN Deep Learning Example**

Hugely popular in image recognition



24/96

### **Convolution Example**

• Objective: to extract features from the input data

filter



2

3

convolution

4

Sung Kyu Lim, Georgia Tech (2019)

0

0

window

0

# Pooling

26/96

- objective
  - reduce the feature map dimension and keep the important information
  - types: max, average, sum, etc.



**Rectified Feature Map** 



### **Recurrent Neural Network (RNN)**



### Image **Description** (not Recognition)

- Describe a given image using a sentence
  - Harder than image recognition/classification
  - Competition is ongoing and fierce among researchers



man in black shirt is playing guitar.





two young girls are playing with lego toy.

a young boy is holding a baseball bat.

### **RNN Applications**





29/96

### Simple Image Search





30/96

### **Complex Image Search**



### **Recurrent Neural Network (RNN)**

- What is RNN?
  - Hochreiter & Schmidhuber (1997)
  - A class of ANN where connections between units form a directed cycle.
  - This allows it to exhibit dynamic temporal behavior
- Why RNN?
  - Unlike feedforward neural networks, RNNs can use their internal memory to process arbitrary sequences of inputs
  - Applicable to tasks such as translation, speech recognition, etc





### **Recurrent Neural Network**





# Generative Adversarial Network (GAN)



### https://www.youtube.com/channel/ UCvX15F7CzUMqf8P7sHtWATA



### Ian Goodfellow: Inventor of GAN

Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio

"Generative Adversarial Nets"

Int. Conf. on Neural Information Processing Systems, 2014.



### Main Idea

- Two neural networks contest with each other in a game
  - Generator generates fake data, hoping to fool discriminator
  - Discriminator evaluates them for authenticity


# **GAN Training**

- In case we deal with image data:
  - The generator takes in a <u>random vector</u> and returns a fake image.
  - This fake image and the real dataset are fed to the discriminator.
  - The discriminator picks one real image and the fake image and returns probabilities, a number between 0 (fake) and 1 (real).



### These Are Fake Photos by GAN



## GAN Can Do Others, Too



39/96

# Text-to-Image Translation with GAN

The small bird has a red head with feathers that fade from red to gray from head to tail



This bird is black with green and has a very short beak



Stage-I images

Stage-II images

### **GAN Can Cross Domains**

41/96





Monet  $\rightarrow$  photo





Summer 📿 Winter



summer  $\rightarrow$  winter



winter  $\rightarrow$  summer

## **Face Aging Prediction**



# Next? Yup, Videos

#### https://www.youtube.com/watch?v=8AZBuyEuDqc







# Autoencoder



# **Anomaly Detection**

45/96

- Definition
  - Identification of rare items, events or observations
  - They raise suspicions by differing significantly from the majority of the data
  - Typically the anomalous items will translate to some kind of problem
  - Can you think of killer apps?



# Video Analytics with ML



# **Applications in Medical Imaging**



# How Fast Is Credit Card Fraud Detection?

48/96



# **Credit Card Fraud Detection DB**

- Offered by Kaggle
  - September 2013 by European cardholders
  - Transactions occurred in two days
  - 492 frauds out of 284,807 transactions
  - Highly unbalanced, the positive class (frauds) account for 0.172%
  - Due to confidentiality issues, details for 28 features are hidden





# **Unsupervised Learning**

• No labels in the database, but it learns by itself!



# Autoencoder

- Hidden layer is smaller
  - For dimensionality reduction
  - Divided in to encoder (first half) and decoder (second half)
  - Useful in feature extraction (encoder)
  - Useful in data reconstruction (decoder)
  - Killer apps in image processing
  - Word imbedding uses AE!





# Unet



# **Semantic Segmentation**

- Smart compute vision application
  - Label each pixel with a corresponding class of what is being represented
  - Commonly referred to as dense prediction.



Person Bicycle Background

# **Application in Autonomous Vehicle**

• Needs to be done really fast and accurately!



54/96

# **Liver Segmentation**



# **CT and MRI-based Imaging**





# **Unet: U-shaped CNN Autoencoder**



Sung Kyu Lim, Georgia Tech (2019)

57/96



# 3. 기계학습 교수법 및 코딩 실습의 예



- RNN으로 주가 변동 예측하기
- Azure로 붓꽃 판별하기



# RNN으로 주가 변동 예측하기



#### Amazon



60/96

### Some Hate Amazon...

#### 61/96



Amazon creates less than half as many jobs as local brick and-mortar stores do. This means the more Amazon grows and crowds out other businesses, the fewer jobs available.



Headquartered in Seattle, Amazon spends next to nothing in the communities where most of its customers live. It doesn't need local printers, designers, lawyers, or bankers. Except for a small amount the company pays to delivery drivers and thirdparty sellers, all of the money that people spend at Amazon leaves their local economy.

Locally owned businesses are by definition headquartered in their community, and they have a proven record of growing the local economy. Studies have found that as local retailers add employees and create local supply chains (by buying goods and services locally), they channel about half of every dollar in sales back into the area.

while local retailers are engines of economic activity, spending their revenue at a wide variety of other businesses in the community, Amazon merely extracts money, leaving little behind.



Property and sales taxes are the main source of funds for our schools and public services. If local businesses are squeezed out by Amazon, households will have to shoulder a higher tax burden.

#### COMMUNITY





Amazon isn't involved in the communities where the majority of its customers live. It doesn't give to local charities or help solve local problems in these places. It contributes nothing to the vitality of our streets and neighborhoods. Most small businesses are **deeply engaged in** their communities, giving almost twice as much to local causes as big businesses. Studies show that places with vibrant local businesses have **livelier streets**, stronger social networks, and more active citizens.

How we choose to direct OUR spending shapes the future of the place we live – and how interesting, special, and healthy it will be.

# Amazon's New Cash Cow





**Competitive Positioning of Players in the Cloud** 



Source: Synergy Research

# Amazon Stock

#### MARKETS d CHART OF THE DAY-

#### VALUE OF \$1,000 INVESTED IN AMAZON

Value of \$1,000 invested at the closing price on May 15, 1997



SOURCE: Yahoo Finance. Prices adjusted for splits and dividends.

**BUSINESS INSIDER** 

# **Amazon Stock Price Database**

- 4,529 daily stock price info
  - From 11/21/2000 to 11/21/2018
- Columns
  - Date: Daily Date
  - Open: Opening price of day
  - High: High price of day
  - Low: Low price of day
  - Close: Closing price of day
  - Adj Close: Adjusted close



64/96

### 1. stock-price.py (1/13)

#### # import packages

import numpy as np import pandas as pd import matplotlib.pyplot as plt from keras.models import Sequential from keras.layers import LSTM, Activation, Dense

```
# global constants and hyper-parameters
TIME_STEP = 3
MY_NUM_NEURON = 256
MY_CUTOFF = 0.7
MY_EPOCH = 10
MY_BATCH = 64
```

### 1. stock-price.py (4/13)

```
# display the logarithm of returns
change = raw_DB.pct_change()
log_return = np.log(1 + change)
print('\n== LOG-RETURN OF THE LAST 10 DAYS ==')
print(log_return.tail(10))
```

```
plt.show()
```

```
# scaling with z-score: z = (x - u) / s
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaled_DB = scaler.fit_transform(raw_DB)
```

#### fit\_transform()

```
67/96
```

```
# conducts data centering
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

```
# we must use 2D array
my_array = [[1], [2], [3], [6]]
x = scaler.fit_transform(my_array)
print(x)
```

```
# converts scaled data back to original
y = scaler.inverse_transform(x)
print(y)
```

### 1. stock-price.py (10/13)

```
# model training and saving
model.compile(loss = 'mse', optimizer = 'adam',
        metrics = ['accuracy'])
model.fit(X train, Y train, epochs = MY EPOCH,
        batch_size = MY_BATCH, verbose = 1)
model.save('chap1.h5')
```

# Adam Optimizer

- Adam: Adaptive moment estimation
  - Keeps separate learning rates for each weight
  - Exponentially decay average of previous gradients
  - Fairly memory efficient since it doesn't keep a history of anything
  - Work well for both sparse matrices and noisy data
  - Seems promising for the stock market data.
  - Works well with little tuning of hyperparameters





### **Exercise Questions**

- Q1: Examine the chap1.h5 file.
- Q2: Try other company stock data (GE, Microsoft, Apple, Google).
- Q3: Try sigmoid activation. What is the impact?
- Q4: Tune the MY\_NUM\_NEURON parameter. What is the impact?
- Q5: Tune the TIME\_STEP parameter. What is the impact?



# Azure로 붓꽃 판별하기









# Iris Classification

Perhaps the best-known example in the field of machine learning ۲

iris versicolor

- The aim is to classify iris flowers among three species
- From measurements of length and width of sepals and petals

#### iris setosa

#### iris virginica sepal sepal petal petal petal sepal
#### **UCI Iris Flower Dataset**



- 150 data with 5 features
  - Petal Length, Petal Width, Sepal Length, Sepal width and Class (Species)
- Goal is to predict class given the 4 dimensions
  - Classical classification problem

#### **Overview of the Model**



Sung Kyu Lim, Georgia Tech (2020)

#### **Azure ML Design Flow**

- 4 major steps
  - Data acquisition > Data preparation > Model training and evaluation > web deployment



#### Sung Kyu Lim, Georgia Tech (2020)

#### **Data Acquisition**

- Search for My Datasets menu in the search window.
- Drag and drop <u>iris.csv</u> module onto the canvas on the right.
- Right click <u>iris.csv</u> module and select dataset > visualize.
  Examine the dataset stats.

iris 🕽 iris.csv 🔰 dataset					
rows 150	columns 5				
	F1	F2	F3	F4	label
view as	Juliu	alla.	h.dh.	Laha	Ш
	5.1	3.5	1.4	0.2	lris-setosa
	4.9	3	1.4	0.2	lris-setosa
	4.7	3.2	1.3	0.2	lris-setosa
	4.6	3.1	1.5	0.2	lris-setosa
	5	3.6	1.4	0.2	lris-setosa
	5.4	3.9	1.7	0.4	lris-setosa
	4.6	3.4	1.4	0.3	lris-setosa
	5	3.4	1.5	0.2	lris-setosa
	4.4	2.9	1.4	0.2	lris-setosa

- Click <u>K-Means Clustering</u> module.
- Change the number of centroids to 3.
- Leave other options as default.

Properties Project		
K-Means Clustering		
Create trainer mode		
Single Parameter 🔹		
Number of Centroids		
3		
Initialization		
K-Means++ ▼		
Random number seed		
Metric		
Euclidean 🔻		
Iterations		
200		
Assign Label Mode		
Ignore label column		

 Right click <u>Train</u> <u>Clustering Model</u> module and visualize the result.



- Run the experiment.
- Right click <u>Select Columns in</u> <u>Dataset</u> module and visualize the result.

RUN

ris 🔉 Sele	ect Columns in D	ataset <b>&gt;</b> Results dataset		
rows 45	columns 2			
	label	Assignments		
view as	hi -	lin -		
	lris-virginica	2		
	lris-setosa	1		
	lris-setosa	1		
	lris-versicolor	0		
	lris-versicolor	0		
	lris-setosa	1		
	lris-setosa	1		
	lris-setosa	1		
	lris-virginica	2		
	Iris-versicolor	0		

• Right click **Evaluate Model** module to visualize the result.





#### Web Deployment

 Click SET UP WEB SERVICE button on the bottom and select Predictive Web Service

menu.



• Newly built model is shown.



#### Web Deployment

- Run the experiment.
- Click DEPLOY WEB SERVICE bottom on the bottom.



• Click Test-preview button.



#### Homework

- 1. Use <u>Edit Metadata</u> module to drop <u>F4</u> column while running Kmeans clustering. What is the impact?
- 2. Replace <u>Multiclass Logistic Regression</u> module with <u>Multiclass</u> <u>Neural Network</u> module. Which one performs better?
- 3. Replace <u>Multiclass Logistic Regression</u> module with <u>Multiclass</u> <u>Decision Forest</u> module. Which one performs better?
- 4. Use <u>Select Columns in Dataset</u> module to drop <u>F4</u> column while running multi-class logistic regression. What is the impact?
- 5. Try changing the split ratio and see the impact.
- 6. What happens if we do not randomize the split process?



# 4. 기계학습 관련 진행 연구



• 회로설계에 적용된 기계학습

### **Clock Routing In Digital Circuit**

• Make electrical connects to all sequential elements in the circuit



sequential elements (red)



clock tree (green)

Sung Kyu Lim, Georgia Tech (2020)

#### **Two Clock Trees**

• Setting is VERY important and requires <u>years</u> of experience

feature	value	
Target skew	0.13ns	
Max fanout	195	
Max cap (trunk)	0.04pF	
Max cap (leaf)	0.10pF	
Target slew (trunk)	0.23ns	
Target slew (leaf)	0.26ns	
Target latency	0.4ns	
eGR metal usage	1, 2, 3, 4	
Cell density	0.6	

#### tree 1 settings

feature	value	
Target skew	0.08ns	
Max fanout	175	
Max cap (trunk)	0.03pF	
Max cap (leaf)	0.07pF	
Target slew (trunk)	0.21ns	
Target slew (leaf)	0.03ns	
Target latency	0.2ns	
eGR metal usage	1, 2, 3	
Cell density	0.7	

tree 2 settings

### **Very Difference Outcome**

• Quality is very different



Power: 21.8mW	WL: 37.5mm
Skew: 0.15ps	Latency: 0.55ps



Power: 72.3mW	WL: 76.4mm
Skew: 0.13ps	Latency: 0.87ps

#### **ML-based CTS Prediction**



#### **Our GAN-based Flow**



#### **Our DB: 3000 Placements from 7 Ckts**



#### Our DB: 3000 Clock Net from 7 Ckts



#### Our DB: 3000 Global Routing from 7 Ckts



## Why Images?

- Extremely useful
  - In handling UNSEEN netlist





-1

0

1

2

3

#### **GAN-Generated Data**

• Our generator became very smart



#### **Gan-Optimized Clock Tree**



(a) GAN-CTS optimized



(b) commercial auto-setting

#### Conclusions

- 1. 인공지능 (AI) 기계학습이란?
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