Deep learning based Medical Image Segmentation

Sanghyuck Lee

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12th Oct, 2022

Contents

To Do List from Previous Seminar

- 개인 연구 : Related Work – Pilot survey 진행 (목표 : 데이터셋 및 비교 알고리즘 구체화)
- SW중심대학지원사업 : 특허 출원 계속 진행
- TAO 연구 : Activity 논문 회신, Label 데이터 수신, nvidia 개발 환경 세팅
- 졸업논문 : minor 수정 작업, 발표 자료 수정, IEEE Access 양식에 맞춰 작성

Overall Progress

Problem

- Deep learning based Medical Image Segmentation

Related Works/Survey (counterparts)

- 2021 & 2022 Medical Image Computing and Computer Assisted Intervention (MICCAI)
- IEEE Transactions on Medical Imaging (TMI) (21.01~22.09)

Experiments

- Experiment

Analysis

- Analysis

Proposal

- Proposal

Post-experimental analysis

- Post exp

Conclusion

- Conclusion

Introduction

- Automatic segmentation of medical image is a essential setp in the quantitavitve diagnosis of many diseases, such as A task, B task, C task, …

Related Work

Pilot survey (Dataset & Counterparts)

- Last two years of MICCAI and TMI → Segmentation (315 papers)
- 60 / 315 papers completed
- Tasks: Ultrasound (cardiac, breast), X-ray (cardiac), Colonoscopy (polyp), Microscopic (cell), Fundus (eye), Dermoscopic (skin)
- Scope: Single type datasets (one specific task) or Multiple type datasets (multiple medical image type)

산학협력프로젝트(SW중심대학지원사업)

산학-2 실적 현황

- 국제 논문 2편 :
  - 2022 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia) 2건 게재 승인 (등록 완료, 출장계획서 작성중, 10.27~10.28 여수 출장 계획(이상혁, 조성현))
- 특허 2건
  - 2건 명세서 초안 검토중

TAO 연구 (CAU Hospital & NVIDIA)

Activity & Treatment

- Activity: 재작성 진행중
- Treatment
  - Label 데이터 수신 대기중
  - 개발환경 세팅: nvidia driver, docker, singularity 설치 및 학습 진행중

졸업 논문

- 졸업 논문 : minor 수정 작업 진행 중
- 발표 자료 : 기존 자료 기반 수정 계획 중
- IEEE Access : Method 작성까지 완료

To-do list

- 개인 연구 : Related Work – Pilot survey 계속 진행 (목표 : 데이터셋 및 비교 알고리즘 구체화)
  - Survey와 함께 결정내려야할 혹은 고민해야할 사항
    - Survey 계속 진행하면서, 2D(공부하기에 좋음) vs 3D(실적내기에 좋음) 어떤 방향으로 범위 좁힐지.
    - CT쪽이 domain 강점이 있는데, 다른 2D domain이 괜찮을지.
    - 목표 데이터셋의 범위를 넓게(다수의 질병, 구조물) 혹은 좁게(하나의 질병, 구조물) 가져갈지.
    - 3D로 간다면, TAO 데이터셋에 집중하는 것이 좋을것.
- SW중심대학지원사업 : 특허 출원 계속 진행
- TAO 연구 : Activity 논문 회신, Label 데이터 수신, nvidia driver, docker, singularity 설치 및 학습 진행
- 졸업논문 : minor 수정 작업, 발표 자료 수정, IEEE Access 양식에 맞춰 나머지 섹션 작성

Thank you

Multimodal Early Fusion Transformer for stock price prediction

Tae-Won Lee

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12th Oct, 2022

To Do List from Previous Seminar

이번 주

- 졸업논문 ppt 작성
- Shapiro test results

Overall Progress

Problem

- Stock Price Prediction
- Low Accuracy

Related Works/Survey (counterparts)

- CNN-BiLSTM-AM
- AdvLSTM
- DTML

Experiments

- KDD 17 Datasets

Data 개수 : 2518
Feature : 6개
(Open, High, Low, Close, Volume, Adj Close)

- Metric

Accuracy

Analysis

- Need more information

Proposal

- Multimodal Learning

Post-experimental analysis

- Accuracy improvement (0.506→0.516)
- Ranking mean improvement
- (2.48 →1.72)

Conclusion

- Conclusion

Stock Price Prediction

미래에셋대우, AI 종목 추천 '콰라의 주가예측' 출시

S&P 500 종목의 향후 예측 등락률 제공

MIRAE ASSET 미래에셋대우

Stock prospect suggestion

딥트레이드-KB증권 MOU 체결…"AI가 상승확률 높은 종목 추천"

주가예측 기술로 수익률 상위권 주식 포트폴리오 추천

KB증권

Portfolio recommendation

Core Task

"내 주식 오를까?"…두나무 '증권플러스', AI 차트예측 서비스

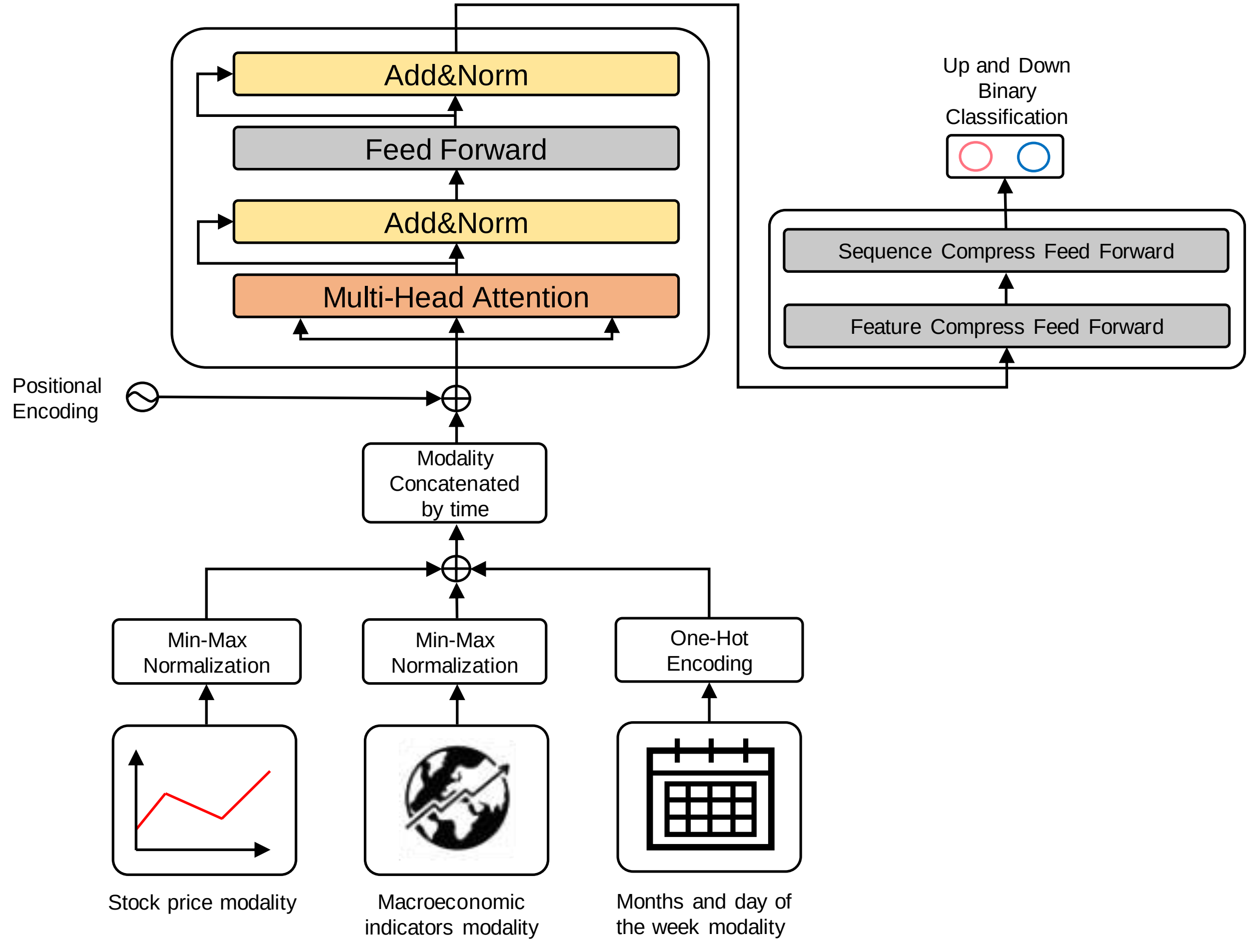
합리적인 투자 전략 수립에 도움

두나무

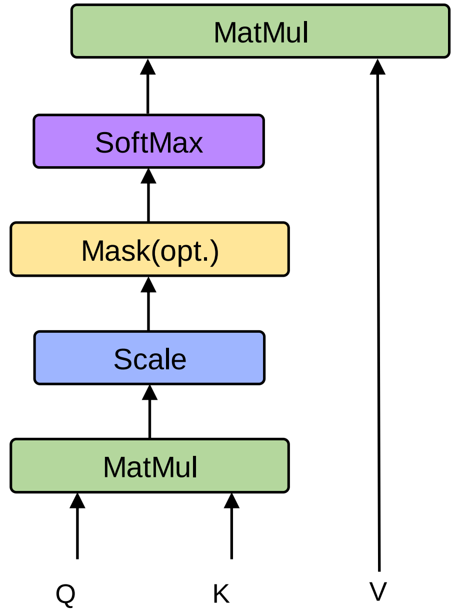
Chart pattern suggestion

Proposed Method

Multimodal early fusion Transformer



Proposed Method



Scaled Dot-Product Attention

Experimental Setting

Comparison algorithm

- CNN-BiLSTM-AM [1]: Hybrid deep learning model
- AdvLSTM [2]: Adversarial Training
- DTML [3]: learning correlation between stocks # Transformer

Performance Measure

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

[1] W. Lu, J. Li, J. Wang, and L. Qin, "A cnn-bilstm-am method for stock price prediction," Neural Computing and Applications, vol. 33, no. 10, pp. 4741–4753, 2021.

[2] J. Yoo, Y. Soun, Y.-c. Park, and U. Kang, "Accurate multivariate stock movement prediction via data-axis transformer with multi-level contexts," in Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, pp. 2037–2045, 2021.

[3] F. Feng, H. Chen, X. He, J. Ding, M. Sun, and T.-S. Chua, "Enhancing stock movement prediction with adversarial training," arXiv preprint arXiv:1810.09936, 2018.

Experimental Result

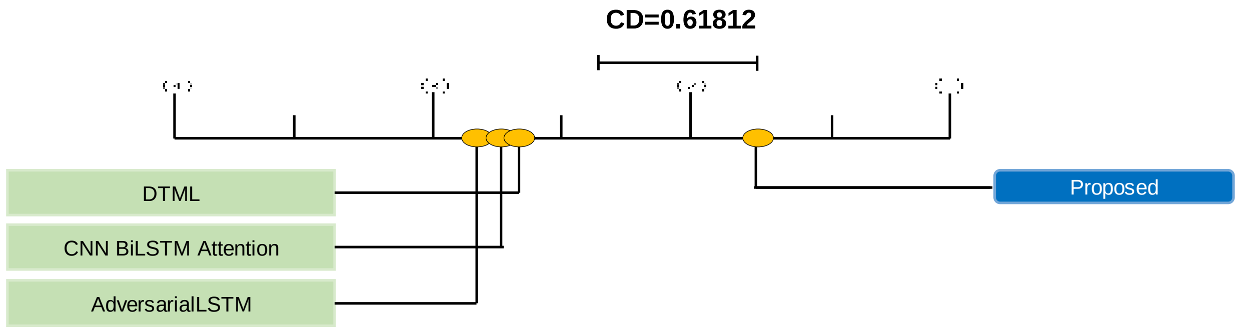
1. Shapiro-Wilk normality test

Group	Shapiro-Wilk Statistic	Critical values (α = 0.05)
Proposed Method	0.9485	0.955
CNN-BiLSTM-AM	0.9791	
AdvLSTM	0.9725	
DTML	0.9727	

2. Friedman test (Multiple comparisons)

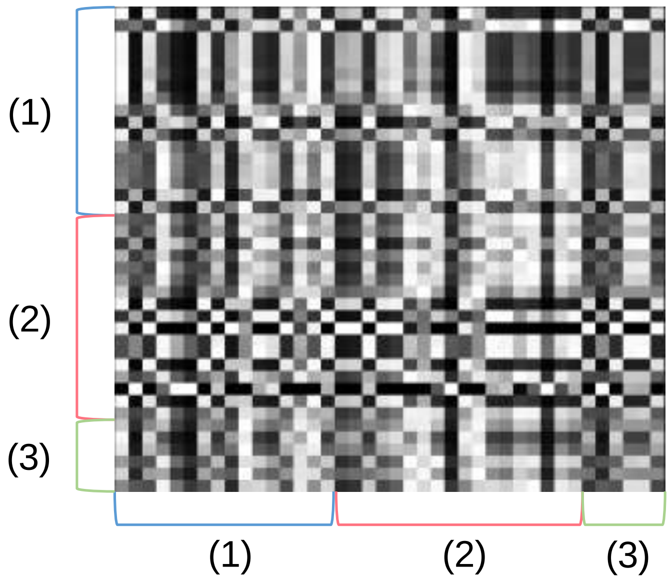
Evaluation measure	Friedman statistic	Critical values (α = 0.05)
Accuracy	24.084	2.557

3. Bonferroni-Dunn test (Post-hoc test)

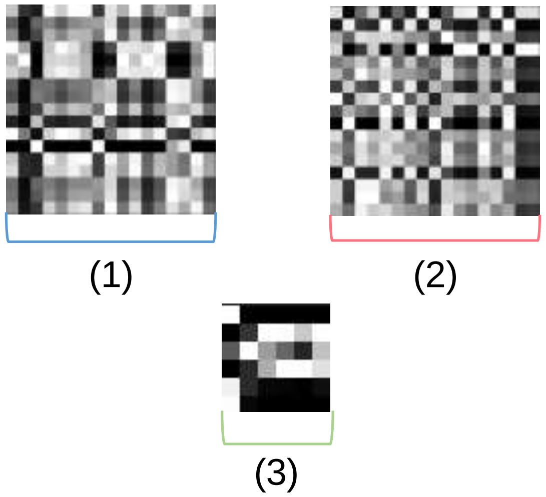


Analysis

	The Number of data with high accuracy
Early fusion method	30
Late fusion method	20



(a) Early fusion



(b) Late fusion

To Do List

다음 주

- 졸업논문 1장, 2장 수정
- IEEE Access -> 졸업논문
- 논문 테이블 및 그림 캡션
- 신경망의 세부적인 그림
- 논문Analysis

Thank you

Effective Music Genre Classification using Early Fusion Convolutional Neural Network with Multiple Spectral Features

Sung-Hyun Cho

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12th Oct, 2022

Contents

To Do List from Previous Seminar

- ✓ IEEE ACCESS 논문 작성
  - ➢ Early Fusion / Late Fusion 정확도 비교 및 장단점 설명
  - ➢ 논문 초안 작성

Overall Progress 2

Problem
- Music genre classification
- Low accuracy

Related Works/Survey (counterparts)
- MGC using single input

Experiments
- Average ranking 1.00
- Passed statistical tests

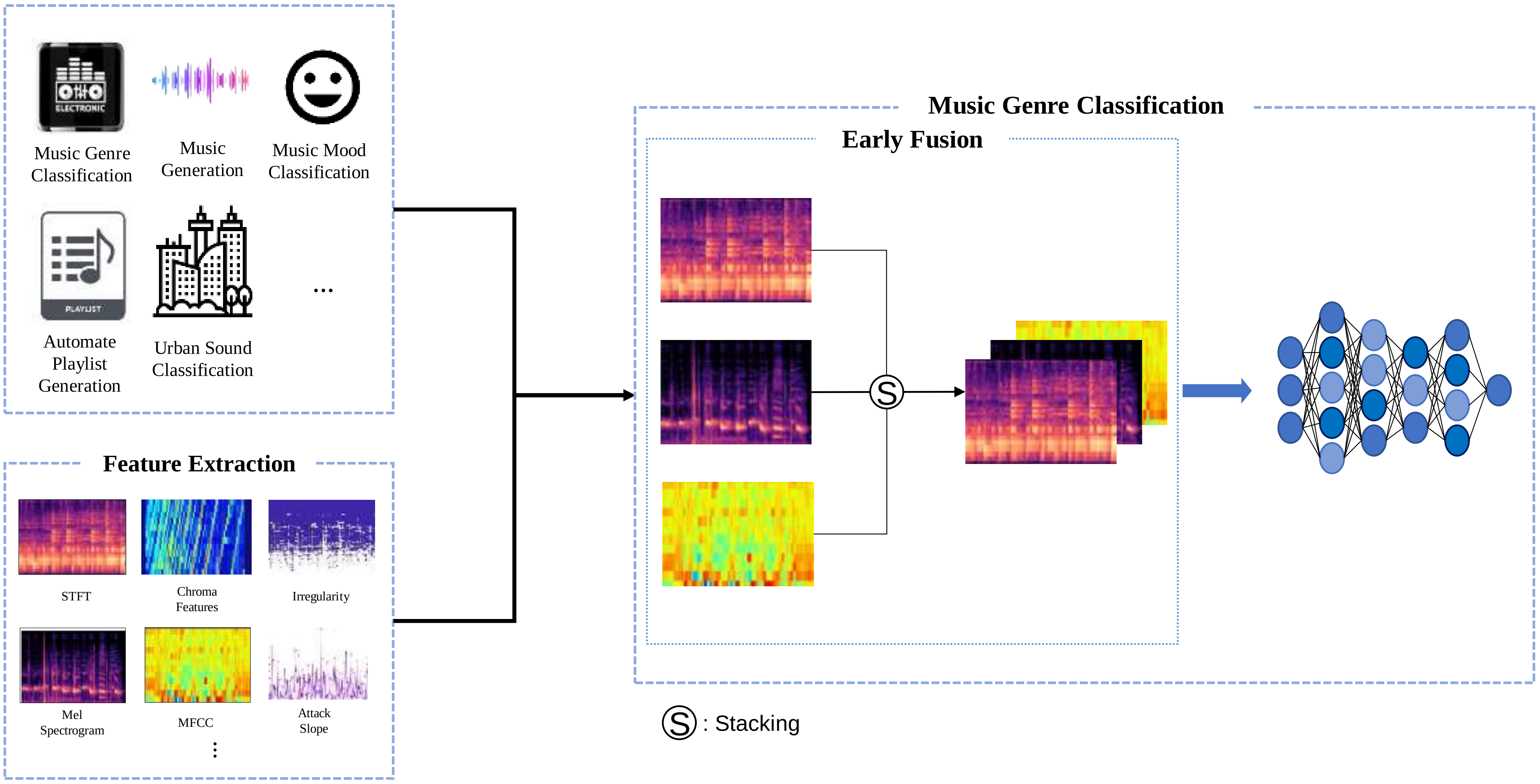
Analysis
- Complement each other's insufficient information by using multiple features

Proposal
- Using STFT, Mel-spectrogram, MFCC

Post-experimental analysis
- Comparison between early fusion and late fusion

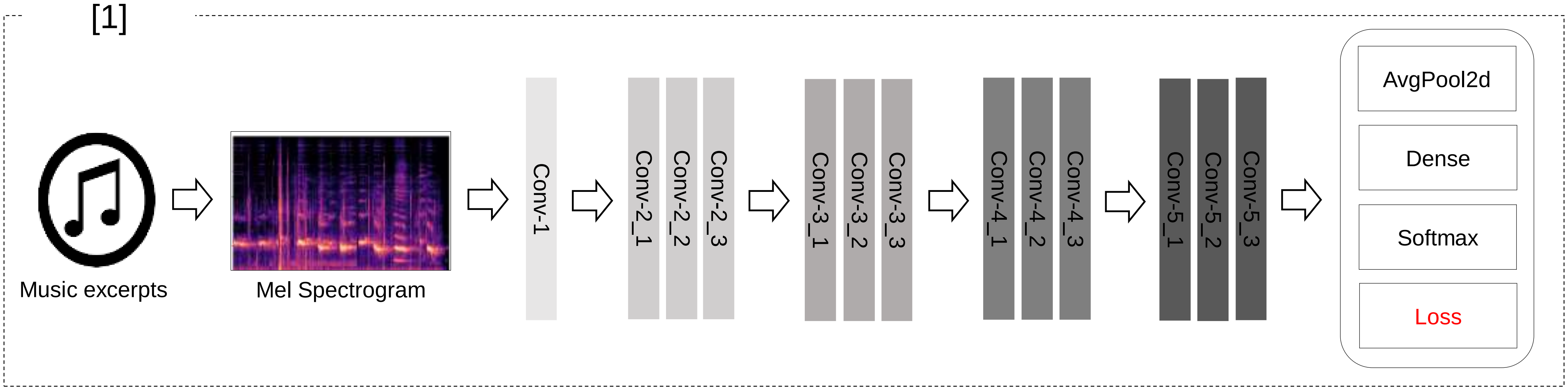
Conclusion
- Using adequate multiple features increase classification accuracy

Introduction



Related Work

[1] Li, J., Han, L., Li, X., Zhu, J., Yuan, B., & Gou, Z. (2022). An evaluation of deep neural network models for music classification using spectrograms. Multimedia Tools and Applications, 81(4), 4621-4647.



$$\boxed{\text{Loss}} = (1 - t) \cdot Loss1 + t \cdot Loss2$$

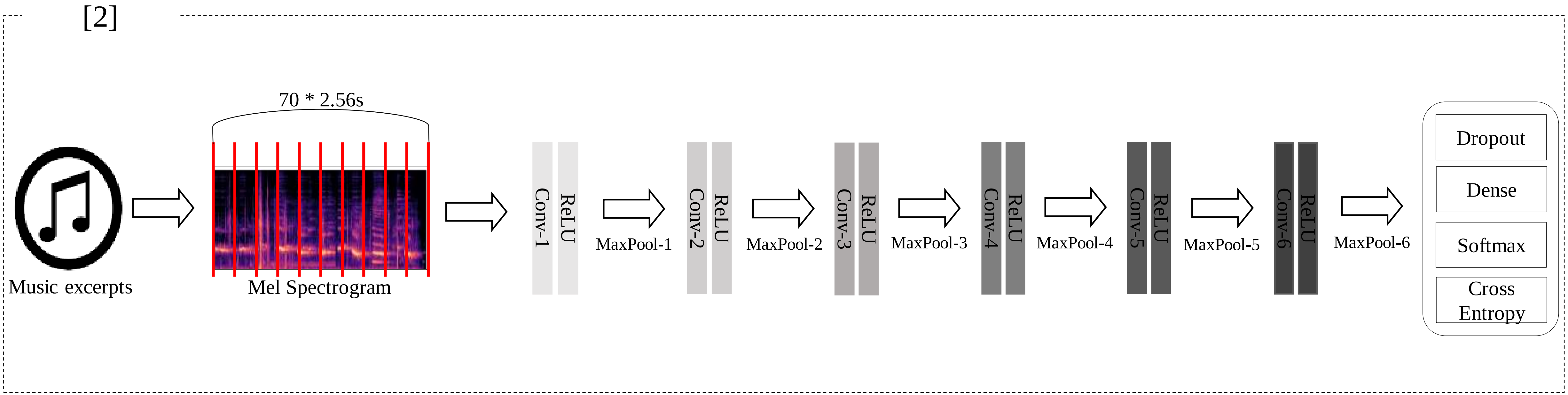
$t = a^{-b}$ $\quad (a : balance\ base, b : balance\ factor)$

$\mathrm{Loss1} = \mathrm{Cross\_Entropy}(\mathrm{y_{true}}(\text{Onehot encoding}), \mathrm{y_{pred}}(\text{Softmax function}))$

$\mathrm{Loss2} = \mathrm{Cross\_Entropy}(\mathrm{y_{true}}(\text{Uniform Distribution function}), \mathrm{y_{pred}}(\text{Softmax function}))$

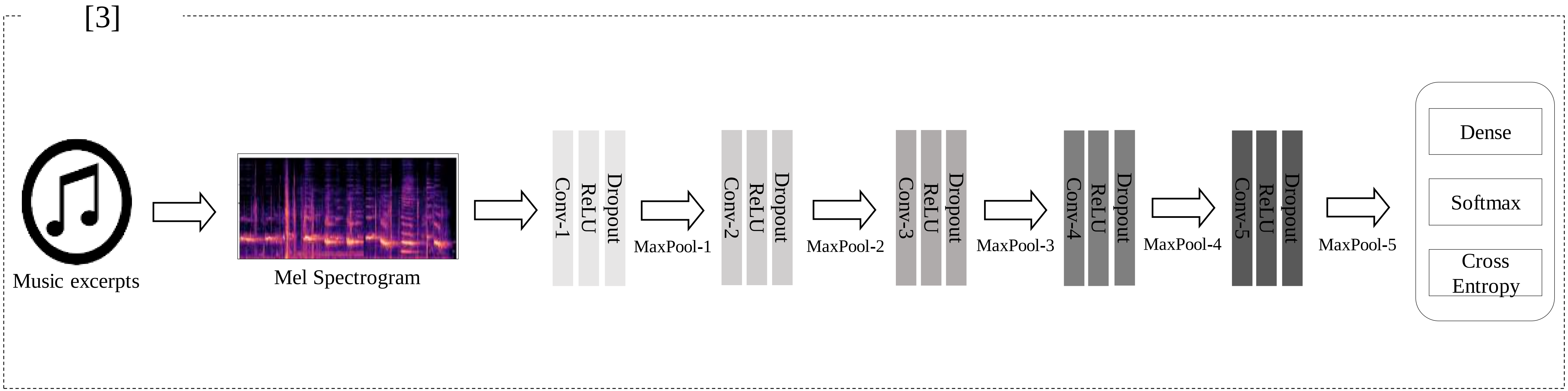
Related Work

[2] Pelchat, N., & Gelowitz, C. M. (2020). Neural network music genre classification. Canadian Journal of Electrical and Computer Engineering, 43(3), 170-173.



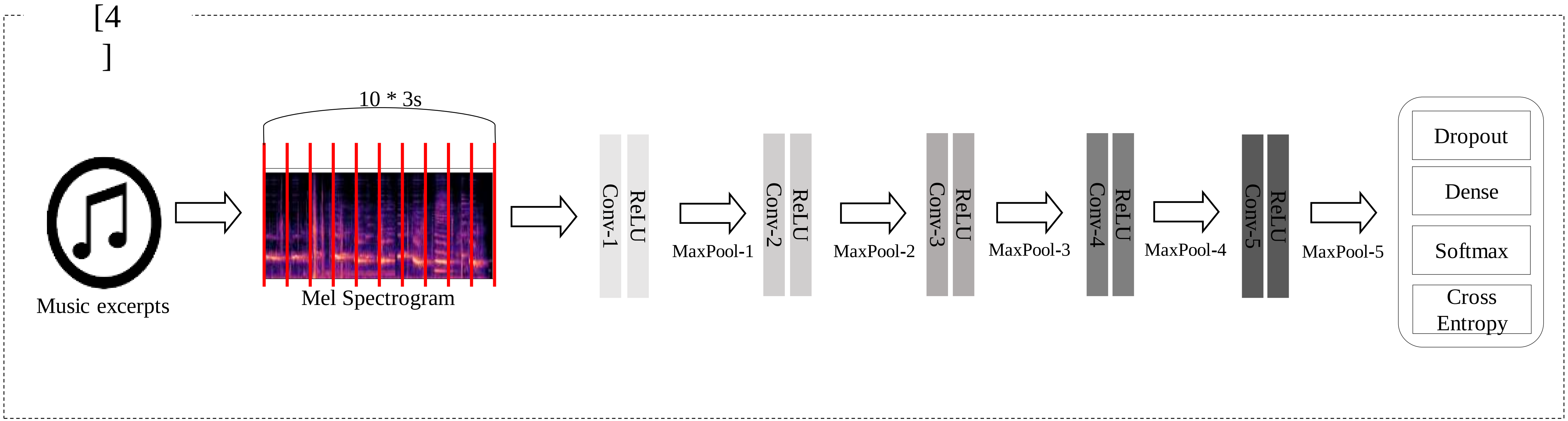
Related Work

[3] Cheng, Y. H., Chang, P. C., & Kuo, C. N. (2020, November). Convolutional neural networks approach for music genre classification. In 2020 International Symposium on Computer, Consumer and Control (IS3C) (pp. 399-403). IEEE.



Related Work

[4] Shah, M., Pujara, N., Mangaroliya, K., Gohil, L., Vyas, T., & Degadwala, S. (2022, March). Music Genre Classification using Deep Learning. In 2022 6th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 974-978). IEEE.



Proposed Method

Model 그림

- Early Fusion 그림 디테일 강화하여 보완 (입력으로 들어가는 데이터 3개에 대한 예제 그림 추가).
- 전체 플로우를 보여주는 그림.
- Early Fusion과 Late Fusion 사이의 차이점을 보여주는 그림 추가
- Early Fusion과 Late Fusion의 러닝 커브(가장 차이가 두드러지는 1개 데이터)

Experimental Settings

Datasets

Dataset	Patterns	Avg. Length	# of Classes	Average Patterns per Class	$\pm$	Standard Deviation
Ballroom	698	30	8	87.250	$\pm$	17.555
Ballroom-Extended	4180	30	13	321.54	$\pm$	195.70
emoMusic-G	744	45	8	93.00	$\pm$	16.1776
Emotify-G	400	43	4	100.00	$\pm$	0.00
FMA-SMALL	7996	30	8	999.500	$\pm$	0.500
GiantStepsKey-G	604	80	23	24.9130	$\pm$	28.0274
GMD-G	1042	300	18	57.89	$\pm$	70.07
GTZAN	1000	30	10	100.00	$\pm$	0.00
HOMBURG	1886	10	9	209.56	$\pm$	134.87
ISMIR04	727	120	6	121.167	$\pm$	95.602
MICM	1137	360	7	162.429	$\pm$	119.717
Seyerlehner-Unique	3115	30	10	311.500	$\pm$	248.349

Cross-Validation for Test Performance

- 10 iterations
- Data Split Ratio: (Train : Test) = (0.8 : 0.2)

Experimental Settings

Hyper Parameter Settings

Model	Batch Size	Epochs	Loss Function	Optimizer	LR	Weight Decay
Proposed	16	60	Cross Entropy Loss	Adam	1e-3	1e-4
[1]	64		Proposed Loss Function			
[2]	128		Cross Entropy Loss			
[3]	32		Cross Entropy Loss			
[4]	32		Cross Entropy Loss			

Performance Measure

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

TP : $True\ Positive$ TN : $True\ Negative$

FP : $False\ Positive$ FN : $False\ Negative$

Evaluates the overall effectiveness of a model

➡ Higher value, Higher Performance

Experimental Results

Model Comparison Based on Accuracy

▼** : 99% significance level
▼* : 95% significance level

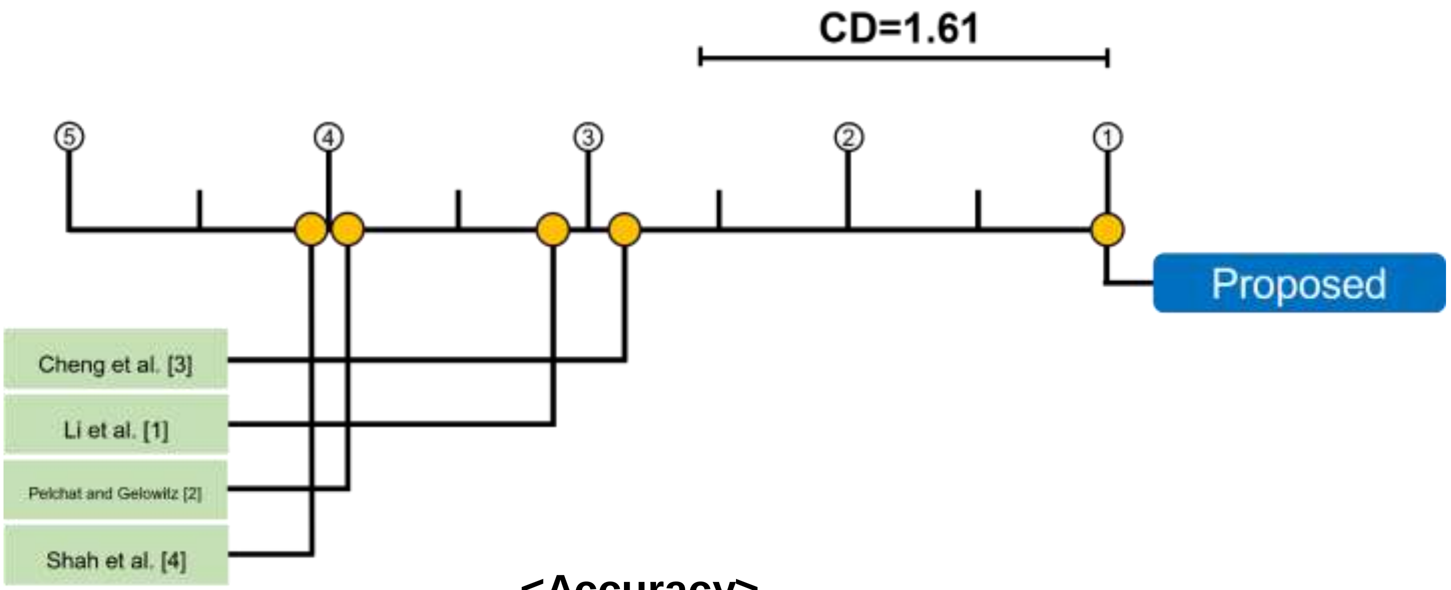
Dataset (Genre)	Proposed	Li et al. [1]	Pelchat and Gelowitz [2]	Cheng et al. [3]	Shah et al. [4]
Ballroom	$\mathbf{58.29 \pm 1.91}$	45.71 ± 2.86▼**	42.43 ± 2.29▼**	48.07 ± 4.79▼**	47.71 ± 4.58▼**
Ballroom-Extended	$\mathbf{85.49 \pm 1.06}$	61.82 ± 3.79▼**	44.68 ± 1.30▼**	62.88 ± 4.70▼**	54.38 ± 5.33▼**
emoMusic-G	$\mathbf{36.04 \pm 0.95}$	27.72 ± 3.50▼**	28.99 ± 1.78▼**	32.95 ± 2.92▼**	31.34 ± 3.66▼**
Emotify-G	$\mathbf{74.88 \pm 2.53}$	62.78 ± 2.70▼**	67.50 ± 4.17▼**	66.00 ± 3.32▼**	65.88 ± 5.62▼**
FMA-SMALL	$\mathbf{57.33 \pm 0.94}$	47.03 ± 1.31▼**	42.19 ± 1.16▼**	46.96 ± 1.62▼**	40.88 ± 1.73▼**
GiantStepsKey-G	$\mathbf{37.27 \pm 1.80}$	28.43 ± 3.15▼**	25.21 ± 2.53▼**	27.19 ± 2.90▼**	24.30 ± 2.11▼**
GMD-G	$\mathbf{67.13 \pm 1.13}$	61.91 ± 3.04▼**	63.44 ± 1.71▼**	39.38 ± 3.36▼**	35.36 ± 6.35▼**
GTZAN	$\mathbf{82.00 \pm 2.24}$	77.50 ± 3.81▼*	63.35 ± 2.08▼**	75.10 ± 3.84▼**	72.50 ± 2.13▼**
HOMBURG	$\mathbf{58.76 \pm 1.15}$	53.49 ± 1.59▼**	51.01 ± 1.51▼**	52.54 ± 2.55▼**	48.15 ± 2.14▼**
ISMIR04	$\mathbf{80.59 \pm 1.41}$	70.96 ± 2.93▼**	67.88 ± 1.70▼**	71.32 ± 1.37▼**	67.67 ± 1.99▼**
MICM	$\mathbf{43.25 \pm 2.32}$	37.81 ± 3.32▼**	39.30 ± 2.21▼**	38.42 ± 3.16▼**	39.34 ± 2.28▼**
Seyerlehner-Unique	$\mathbf{72.57 \pm 1.19}$	63.62 ± 2.56▼**	60.72 ± 2.73▼**	63.50 ± 2.79▼**	61.62 ± 1.70▼**
Total Win / Tie / Lose	48/0/0	16/16/16	3/15/30	15/19/14	5/16/27
Avg . Rank	**1.00**	3.17	3.92	2.83	4.08

Experimental Results

Friedman Test

Evaluation Measure	F_F	Critical Value$(\alpha = 0.05)$
Accuracy	29.133	2.498

Bonferroni-Dunn Test



<Accuracy>

Experimental Results

Comparison to Single Features (GTZAN)

Iteration	All	STFT	Mel-Spectrogram	MFCC
1	**85.50%**	72.50%	76.50%	64.00%
2	**83.00%**	70.50%	79.00%	67.00%
3	**84.00%**	74.50%	78.50%	59.00%
4	**82.00%**	76.00%	80.50%	61.50%
5	**80.50%**	72.00%	76.00%	60.00%
6	**82.00%**	73.00%	76.50%	66.00%
7	**84.00%**	75.50%	74.00%	68.50%
8	**81.50%**	76.00%	80.50%	62.00%
9	79.00%	79.00%	**80.00%**	59.00%
10	**78.50%**	75.50%	78.00%	62.00%
Average Accuracy	**82.00%**	74.40%	77.95%	62.90%

Experimental Results

Model Comparison Based on Accuracy

▼ : 95% significance level

Dataset (Genre)	Early Fusion	Late Fusion
Ballroom	$\mathbf{58.29 \pm 1.91}$	55.86 ± 3.41
Ballroom-Extended	$\mathbf{85.49 \pm 1.06}$	70.35 ± 3.25▼
emoMusic-G	$\mathbf{36.04 \pm 0.95}$	35.77 ± 2.49▼
Emotify-G	$\mathbf{74.88 \pm 2.53}$	72.00 ± 4.05▼
FMA-SMALL	$\mathbf{57.33 \pm 0.94}$	55.07 ± 0.84▼
GiantStepsKey-G	$\mathbf{37.27 \pm 1.80}$	35.29 ± 2.67▼
GMD-G	$\mathbf{67.13 \pm 1.13}$	65.50 ± 3.55
GTZAN	$\mathbf{82.00 \pm 2.24}$	79.00 ± 2.94
HOMBURG	$\mathbf{58.76 \pm 1.15}$	55.53 ± 2.39▼
ISMIR04	$\mathbf{80.59 \pm 1.41}$	79.13 ± 2.39
MICM	$\mathbf{43.25 \pm 2.32}$	41.18 ± 2.94
Seyerlehner-Unique	$\mathbf{72.57 \pm 1.19}$	70.85 ± 2.36▼
Avg . Rank	**1.00**	2.00

Conclusion

Conclusion

- Conducted a novel CNN model with three pipelines.
- Achieve higher accuracy than conventional methods using a single input.

Conclusion

In international Publication (SCI(E))

- Toward a Fair Evaluation and Analysis of Feature Selection for Music Tag Classification, ***IEEE Access,*** 2021, **Co-author**

In International Conferences

- Effective Music Genre Classification using Late Fusion Convolutional Neural Network with Multiple Spectral Features ***ICCE-Asia***, 2022, **1^{st} author**
- An Efficient Neural Network based on Early Compression of Sparse CT Slice Images, ***PlatCon***, 2021, **Co-author**

In Domestic Conferences

- Music Genre Classification Using Multiple Musical Visual Features, ***IEIE***, 2022 , **1^{st} author**
- Music Genre Classification using CNN architecture with feature concatenation, ***KISS Autumn Conf***, 2021, **Co-author**

To Do List

졸업

- Proposed Method 그림 추가
- ~10월 18일(화), 졸업논문 초안 작성
- ~10월 25일(화), 졸업논문 완성
- 11월 2일(수)~11월 8일(화), 졸업논문 발표 (발표 1주일 전 졸업논문의 스프링 제본판 전달)
- 11월 16일(수), 졸업논문 심사보고서 제출 마감

ICCE-Asia

- 10월 28일(금) 09:00~10:20, 발표

To Do List

Patent

- P20220244 (**자동 음악 태그 분류 성능 향상을 위한 음악 특징 선택 시스템 및 방법**)
  - 중앙대학교 시스템에 따르면, P2022024건과 관련된 <u>논문이 21.10.28에 공개</u>된 것으로 확인
  - 발명의 공개에 따른 ‘공지예외’ 주장을 위해 <u>**22.10.28 이전에 출원 완료**</u> 예정

Thank you

Eyeball Volume Estimation

Sujeong Han

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12th Oct, 2022

Contents

To Do List from Previous Seminar

- ✓ Estimation of the Volume of the Left eyeball From CT Images
    - ➢ Measure : MAE (Mean Absolute Error)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y'_i\right|$$

Overall Progress

Problem

- Volume Estimation

Related Works/Survey (counterparts)

- Volume Estimation
- Image data imputation

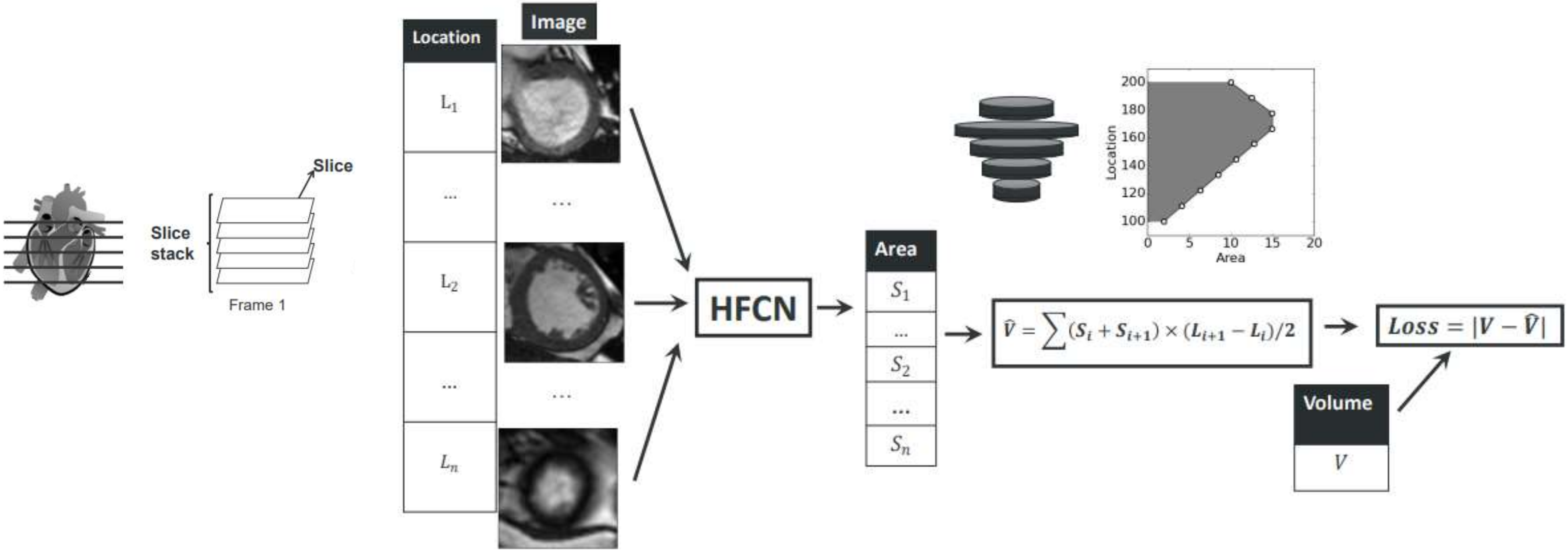
Experiments

Analysis

Proposal

Related Work

Estimating the volume of the left ventricle from MRI images using deep neural networks (IEEE, 2017)



Experimental Settings

Datasets

✓ Eyeball segmentation images from 1,237 patients

✓ Ground Truth : Eyeball Volume of 532 patients

✓ 조건:

- CT 원본이미지에 axial view를 뜻하는 메타데이터를 하나라도 포함하고 있는 환자일 것
- AX1~AX5, AX7까지의 모든 이미지가 있을 것
- 김수영 선생님께서 전달해주신 값이 있는 환자일 것

✓ Input : Eyeball segmentation images from 290 patients

✓ Output : Eyeball Volume

Experimental Results

Patient Number	Ground Truth	Model + People	Pixel Thickness / slice space	Slice
200095	8.27 cc	14.22 cc	1mm	17
101483	8.43 cc	2.54 cc	1mm	7
101483	8.19 cc	2.35 cc	1mm	7
10415	7.89 cc	2.44 cc	1mm	7
10402	7.06 cc	6.33 cc	2.5mm	7
10912	6.69 cc	5.49 cc	1mm	17
101147	7.22 cc	6.13 cc	1mm	17
10561	7.16 cc	7.4 cc	2.5mm	7

Experimental Results

	Ground Truth	Model + People
Min	6.69 cc	2.3 cc
Max	10.8 cc	14.21 cc
Mean±Std	8.37±0.92	6.01±1.32

Ground Truth & Model + People	
MAE	2.5
Corr	0.312

Thank you

Individual Studies

Taekyung Song

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12th Oct, 2022

Contents

To Do List from Previous Seminar

Contents

- ✓ Individual Study
  - ➢ Sementic Segmentation using localized information

- ✓ 갑상선 연구 – 눈꺼풀 길이 추론
  - ➢ 눈의 중앙으로부터 눈꺼풀까지의 길이 분포 확인

Overall Progress

Problem → Related Works/Survey (counterparts) → Experiments → Analysis → Proposal

Problem

- Sementic Segmentation Accuracy

Related Works/Survey (counterparts)

Experiments

Analysis

Proposal

Individual Study

Sementic Segmentation using localized information

Sementic Segmentation using localized information					
no	year	j/c	title	dataset	abstrac
1	2019	*IEEE journa*	Knowledge-aided convolutional neural network for small organ segmentation.		
2	2019	*IEEE/CVF I*	Fine-grained segmentation networks: Self-supervised segmentation for improved long-term visual localization.		
3	2020	*NeuroImage*	An automated framework for localization, segmentation and super-resolution reconstruction of fetal brain MRI.		
4	2020	*IEEE transa*	Attention-Based Dropout Layer for Weakly Supervised Single Object Localization and Semantic Segmentation		
5	2021	*Ieee Access*	Real-time polyp detection, localization and segmentation in colonoscopy using deep learning.		
6	2022	*IEEE Trans*	Weakly-Supervised Surface Crack Segmentation by Generating Pseudo-Labels Using Localization With a Classifier and Thresholding		
7					
8					
9					
10					
11					
12					
13					
14					
15					

산학연6 - 두산산업차량

진행상황(WBS)

과제		2022년 07월					2022년 08월					2022년 09월				2022년 10월				2022년 11월			
세부목표	세부활동	w1	w2	w3	w4	w5	w1	w2	w3	w4	w5	w1	w2	w3	w4	w1	w2	w3	w4	w1	w2	w3	w4
1. CUP & WDA 분석 알고리즘 개발																							
1.1.	전동 지게차 CAN data 취득(산업차량)																						
1.2.	엔진 지게차 CAN Data 취득(산업차량)																						
1.3.	지게차 고장 데이터 취득(산업차량)																						
1.4.	CUP 분석 프로세스 개발																						
1.5.	전동 지게차 CUP 분석 알고리즘 개발(중앙대)																						
1.6.	엔진 지게차 CUP 분석 알고리즘 개발(중앙대)																						
1.7.	WDA 알고리즘 개발(중앙대)																						

산학연6 - 두산산업차량

Correlation-Based Feature Selection

- mass
  ['Left_Traction::LT_Backward_Bit7', 'Left_Traction::LT_Brake_Bit3', 'Pump::Lift_Sensor', 'Left_Traction::Steering_Sensor', 'Monitoring::BDI_Percentage[%]', 'Left_Traction::Accelerator[V]', 'Monitoring::Speed[Km]']

- residual_acceleration
  ['Monitoring::BDI_Percentage[%]', 'Monitoring::Speed[Km]']

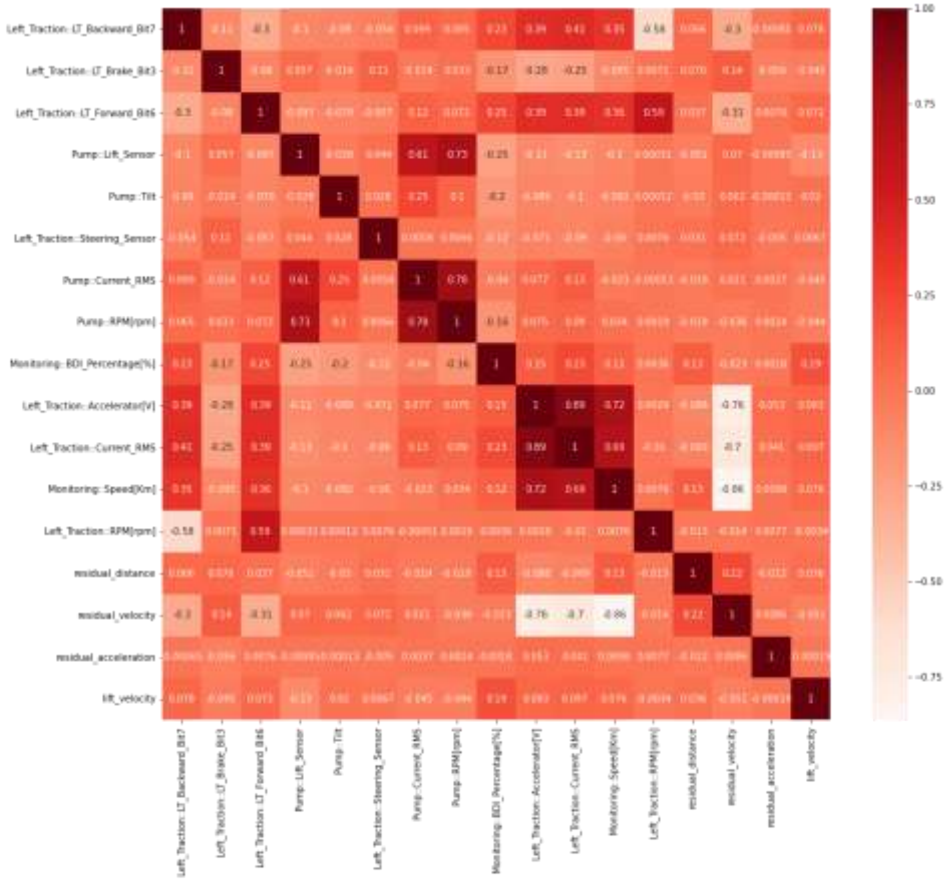
- residual_velocity
  ['Monitoring::BDI_Percentage[%]', 'Monitoring::Speed[Km]']

- residual_distance
  ['Monitoring::BDI_Percentage[%]', 'Monitoring::Speed[Km]']

- turning_angle
  ['Left_Traction::LT_Brake_Bit3', 'Pump::Lift_Sensor', 'Pump::Current_RMS', 'Pump::RPM[rpm]', 'Monitoring::BDI_Percentage[%]', 'Left_Traction::Accelerator[V]', 'Left_Traction::Current_RMS', 'Monitoring::Speed[Km]']

- height
  ['Left_Traction::LT_Brake_Bit3', 'Pump::RPM[rpm]', 'Left_Traction::Accelerator[V]']

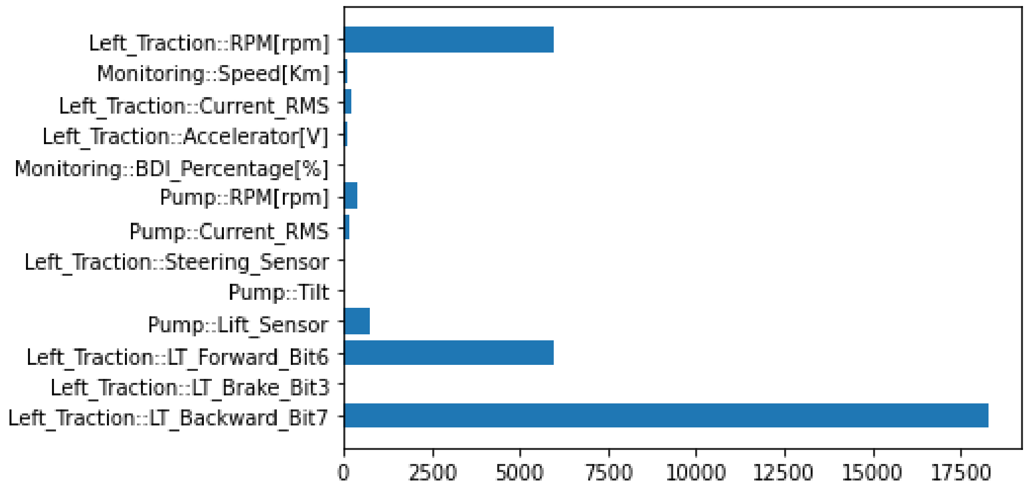
- lift_velocity
  ['Pump::Lift_Sensor', 'Monitoring::BDI_Percentage[%]']



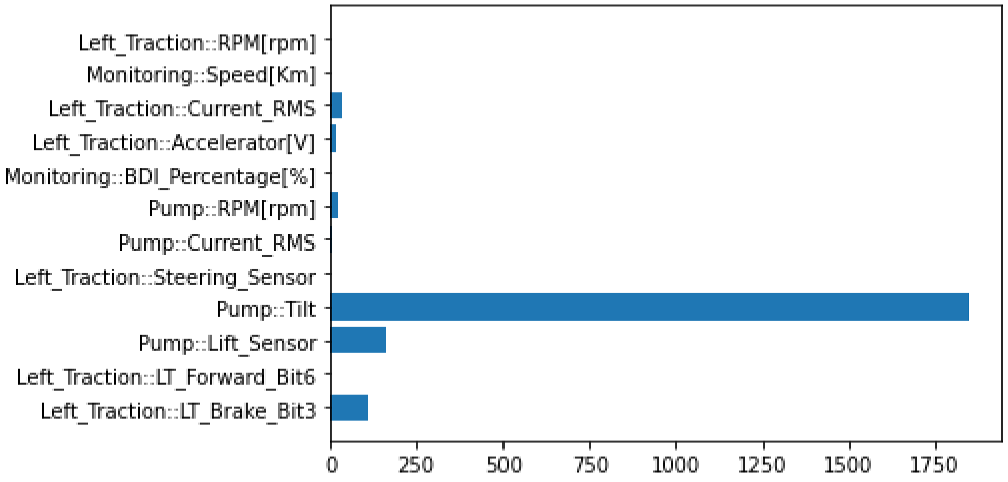
산학연6 - 두산산업차량

Analysis of Variance

F/R Mode (전/후진 모드)



Lift/Tilt Mode



산학연6 - 두산산업차량

전동 지게차 학습 결과

Training	Validation	Priority	Stage5/Electric	평가 항목	평가 기준
1.0	0.999	1	주행 모드	F-1 score	90점 이상
-	-	3	운행환경	F-1 score	90점 이상
2 (kg)	5 (kg)	1	부하	MAE	300kg
1.049	1.159	1	속도	MAE	3km/h
1.830	1.971	2	가속도	MAE	
-	-	2	*급가속/감속 진단 Post processing	-	-
0.003	0.003	1	이동거리	MAE	1m
-	-	2	기어 단수(엔진)	F-1 score	90점 이상
-	-	2	모드 구분(전동)	F-1 score	90점 이상
-	-	2	변속(엔진) (자동/수동)	F-1 score	90점 이상
15.656	30.547	3	선회각도	MAE	10º
0.998	0.891	2	선회 방향	F-1 score	90점 이상
-	-	2	인칭(엔진)	F-1 score	90점 이상
0.989	0.970	1	작업기 모드	F-1 score	90점 이상
34.519 (mm)	38.112 (mm)	1	작업기 상승 속도	MAE	50mm/s
-	-	1	작업기 하강 속도	MAE	50mm/s
1	0.831	2	작업기 전경/후경	F-1 score	90점 이상
0.528	0.588		작업기 높이	MAE	

산학연6 - 두산산업차량

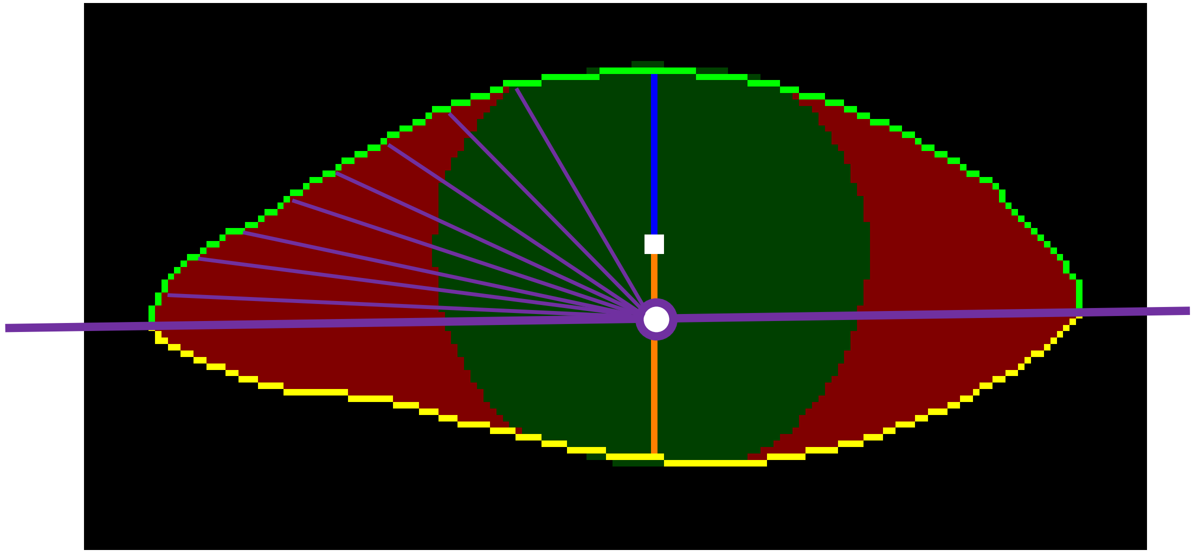
엔진 지게차 학습 결과

Training	Validation	Priority	Stage5/Electric	평가 항목	평가 기준
1.0	0.987	1	주행 모드	F-1 score	90점 이상
-	-	3	운행환경	F-1 score	90점 이상
231 (kg)	639 (kg)	1	부하	MAE	300kg
-	-	1	속도	MAE	3km/h
-	-	2	가속도	MAE	
-	-	2	*급가속/감속 진단 Post processing	-	-
-	-	1	이동거리	MAE	1m
-	-	2	기어 단수(엔진)	F-1 score	90점 이상
-	-	2	모드 구분(전동)	F-1 score	90점 이상
-	-	2	변속(엔진) (자동/수동)	F-1 score	90점 이상
-	-	3	선회각도	MAE	10º
1.0	1.0	2	선회 방향	F-1 score	90점 이상
1.0	0.993	2	인칭(엔진)	F-1 score	90점 이상
1.0	0.986	1	작업기 모드	F-1 score	90점 이상
-	-	1	작업기 상승 속도	MAE	50mm/s
-	-	1	작업기 하강 속도	MAE	50mm/s
-	-	2	작업기 전경/후경	F-1 score	90점 이상
-	-		작업기 높이	MAE	

갑상선 연구 – 눈꺼풀 길이 추론

눈의 모양을 평가하는 metric

- 기존 시도의 문제
  1. 중앙에서 1°씩 $y = ax + b$ 그래프를 그렸을 때
     - 그래프 위에 정확히 일치하는 픽셀이 존재하지 않을 경우
  2. 눈꺼풀 픽셀 개수의 문제
     - 촬영 거리에 따라, 환자의 눈 크기에 따라 픽셀 개수가 유동적



눈의 모양을 평가하는 metric

- 개선 방안
  - 눈꺼풀에 해당하는 픽셀과의 길이 모두 측정
  - 대상: 총 697명 중 572명(reflex 미관측자 제외)

	L_upper	L_lower	L_total	R_upper	R_lower	R_total
Pixel	169.56	239.44	409	167.58	237.47	405.05

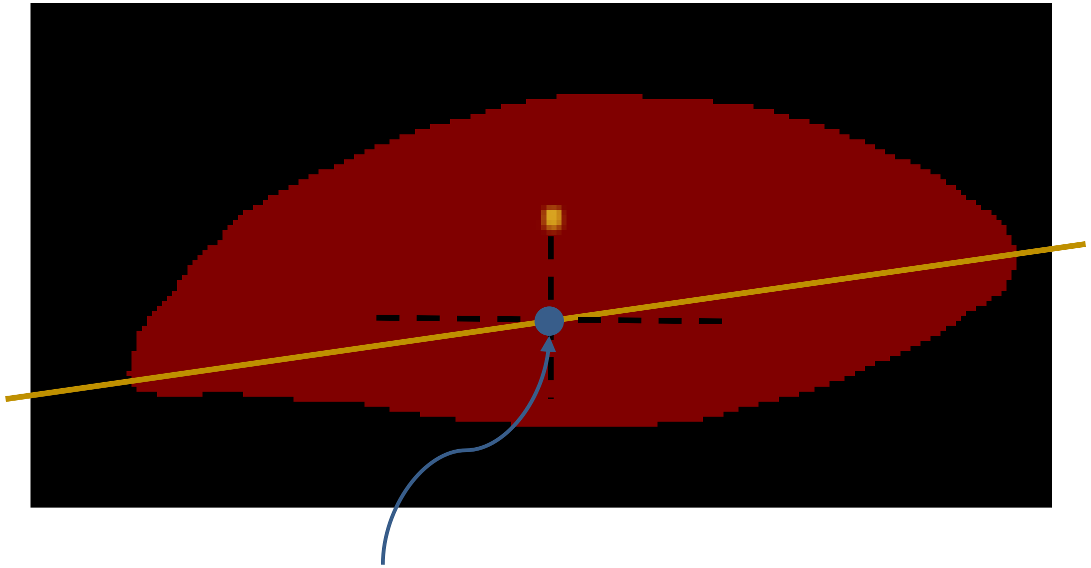
단위: 개

	p_num	L				R			
		L_up_nu	L_lo_nu	L_tota	L_refle	R_up_nu	R_lo_nu	R_tota	R_refle
1	101011	206	298	504	o	217	307	524	o
2	101020	157	223	380	o	155	215	370	x
3	101021	174	252	426	o	169	236	405	o
4	101026	151	220	371	o	142	193	335	o
5	101041	182	269	451	x	188	224	412	o
6	101043	165	248	413	o	173	249	422	o

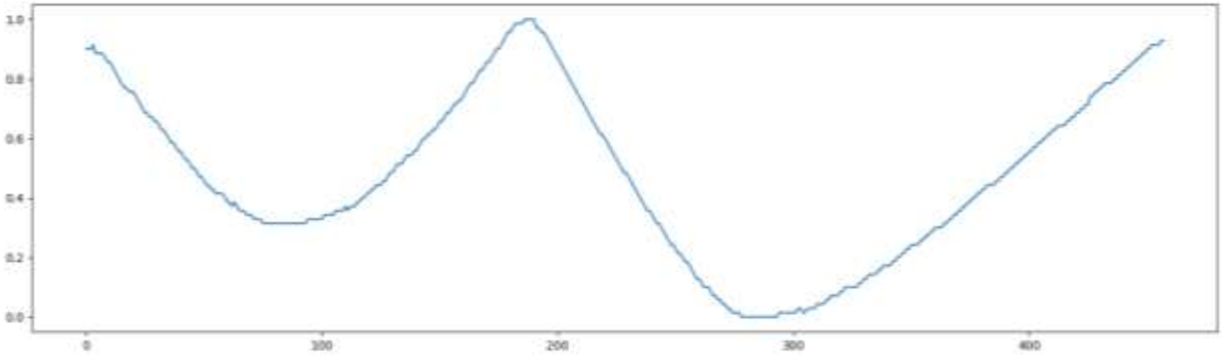
갑상선 연구 – 눈꺼풀 길이 추론

눈의 모양을 평가하는 metric

- Process
  1. 양쪽 눈 끝점을 지나는 선분과 reflex의 중점이 직교하는 포인트 계산
  2. 해당 포인트로부터 눈꺼풀에 해당하는 픽셀과의 거리 계산
  3. 정규화 진행 → 그래프화



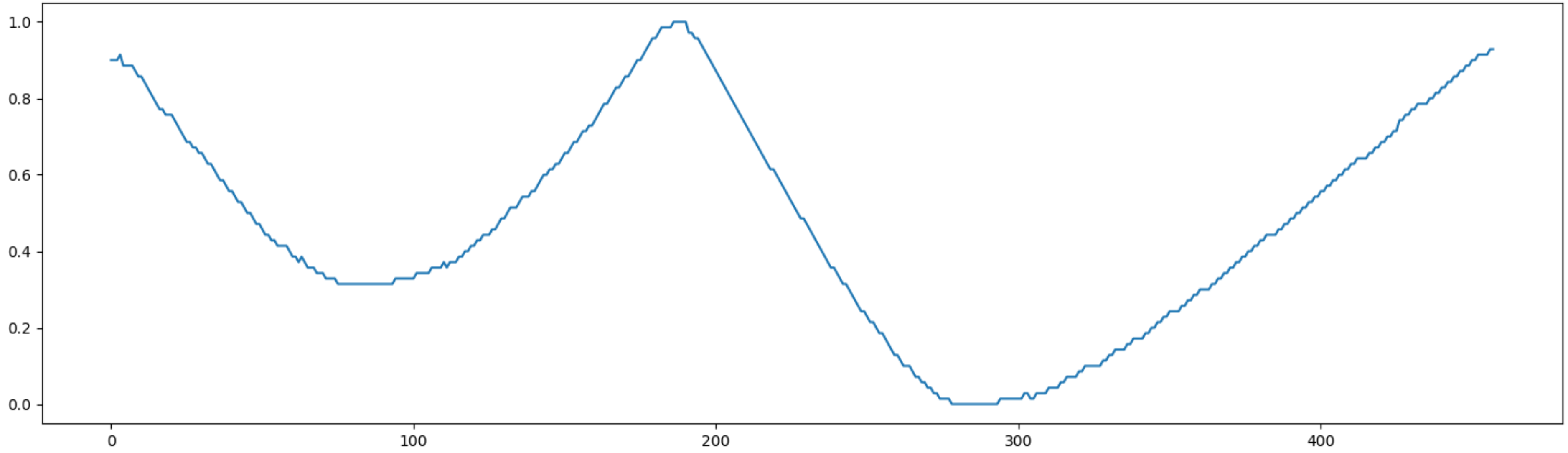
New_eye_center_point

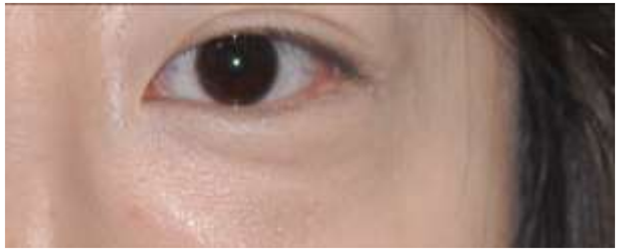


갑상선 연구 – 눈꺼풀 길이 추론

1031_L

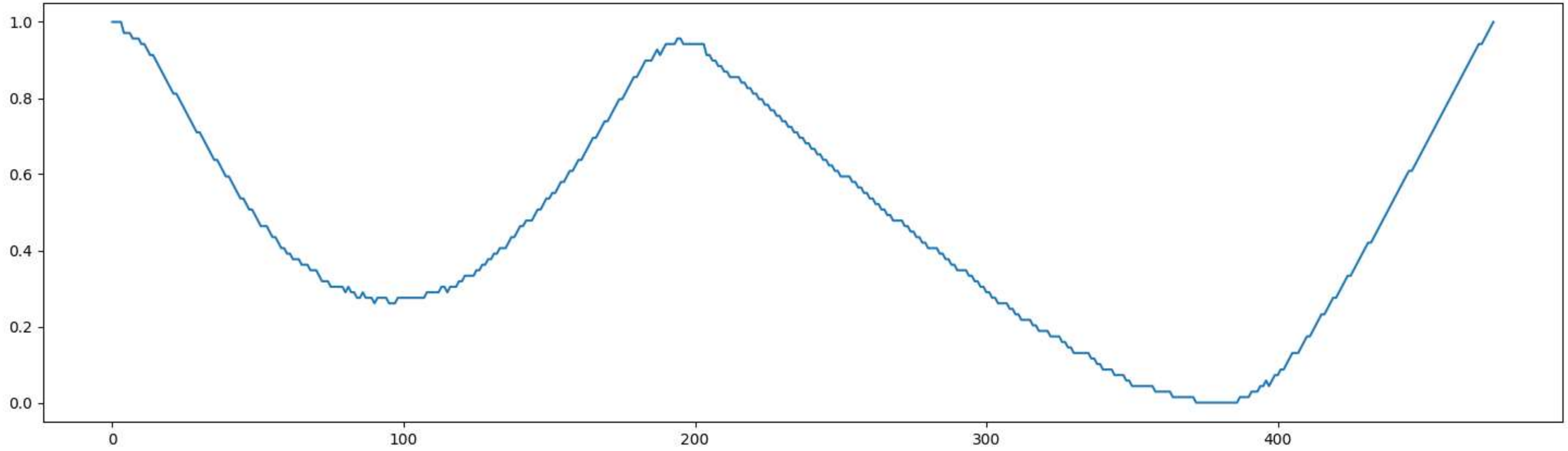
- upper: 190
- lower: 268





1031_R

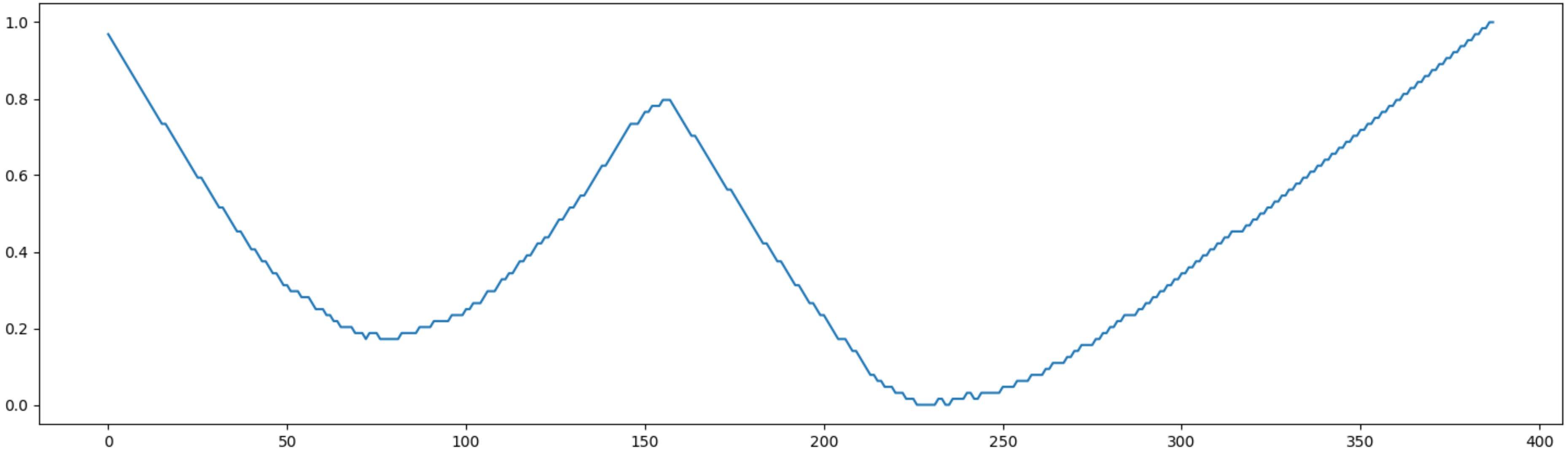
- upper: 194
- lower: 281



갑상선 연구 – 눈꺼풀 길이 추론

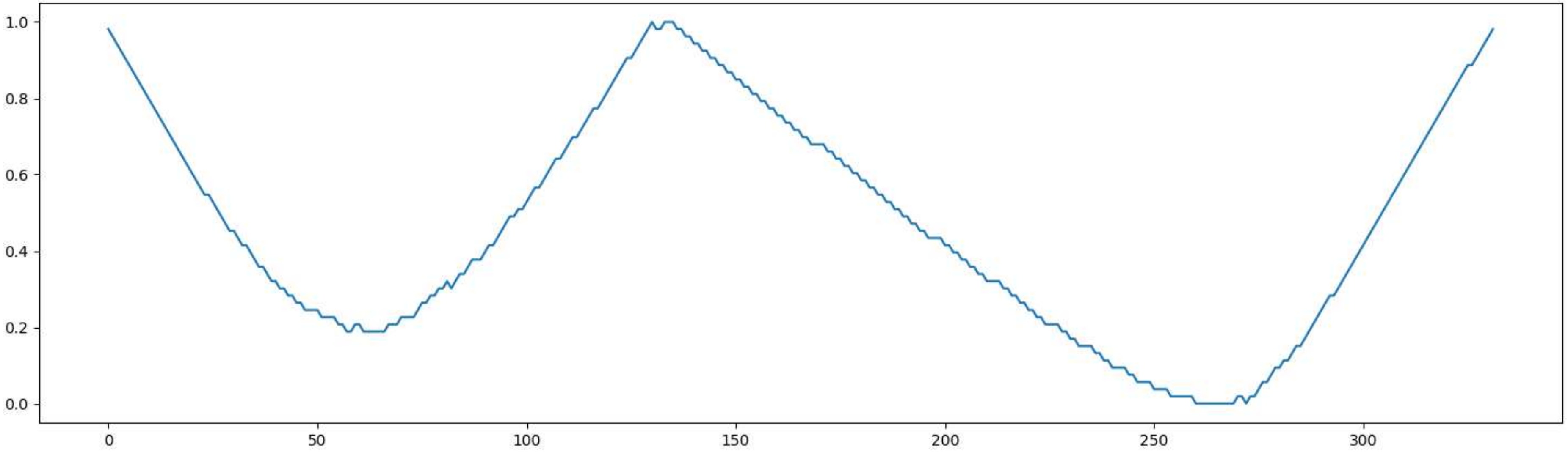
101129_L

- upper: 157
- lower: 231

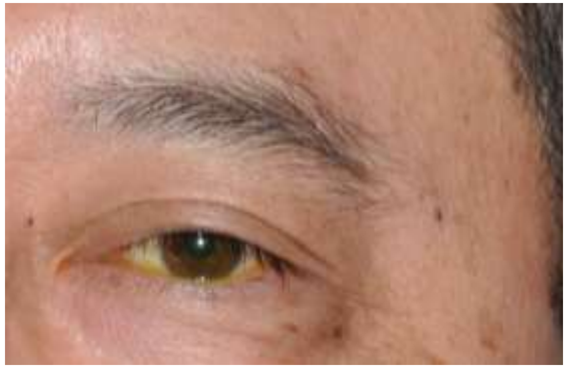


101129_ R

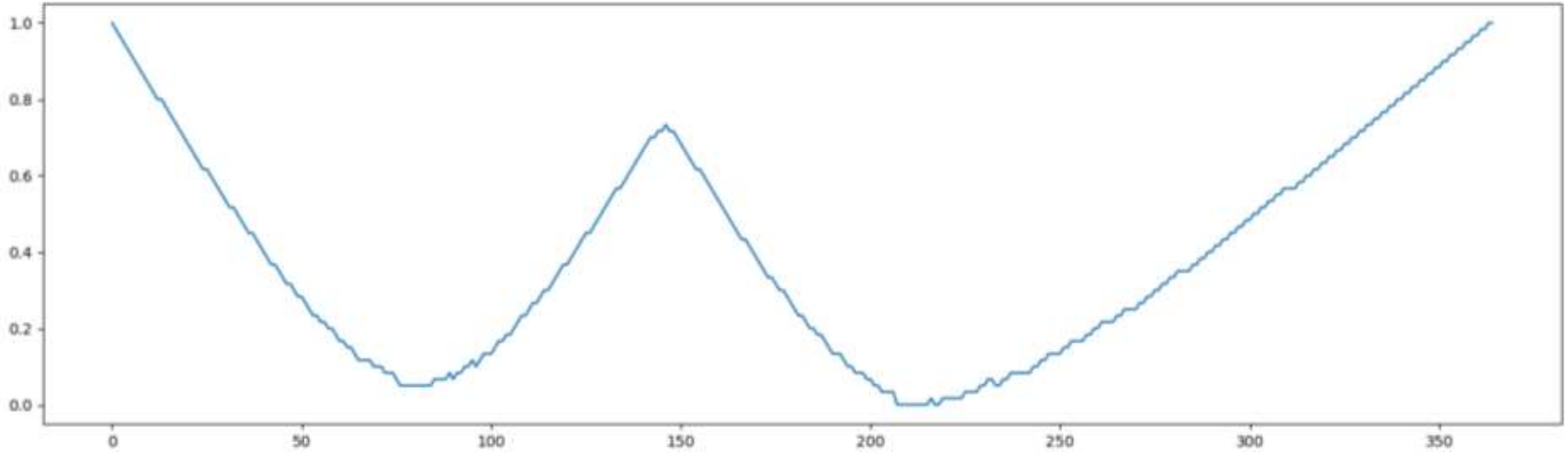
- upper: 134
- lower: 198

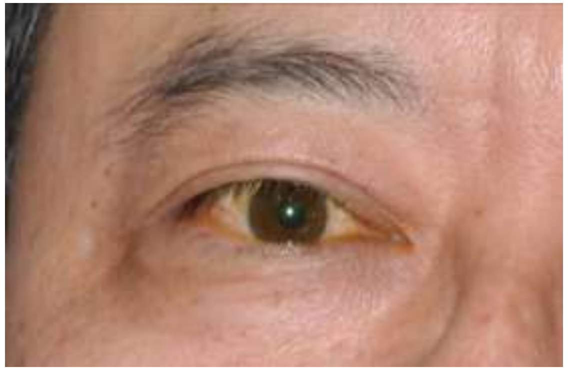


갑상선 연구 – 눈꺼풀 길이 추론

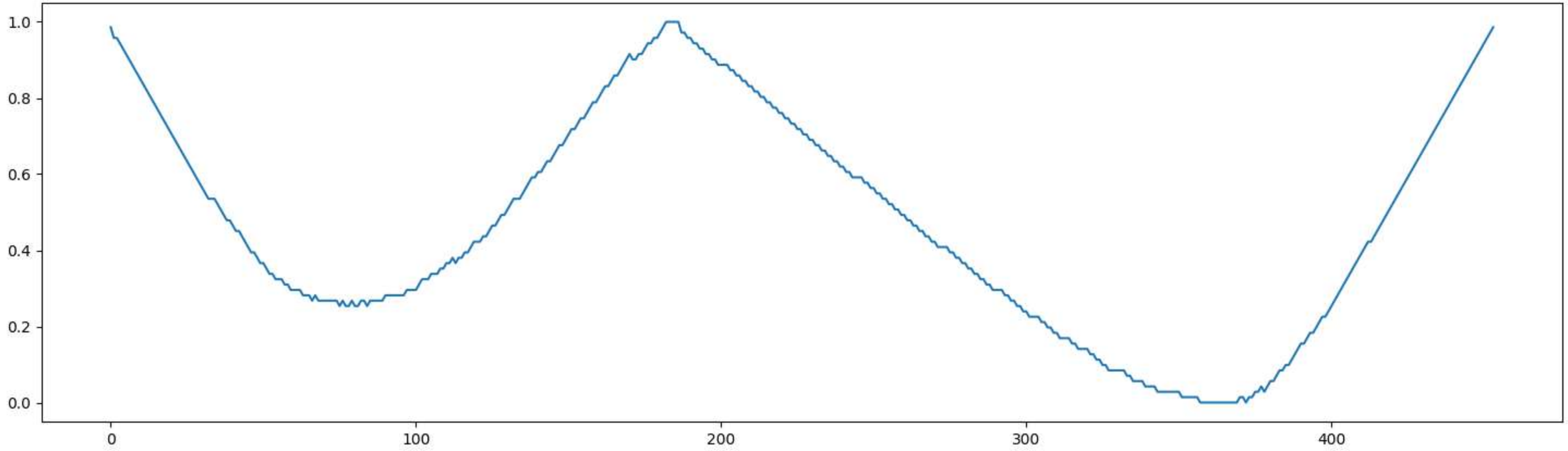


101621_L - upper: 157
- lower: 231





101621_ R - upper: 134
- lower: 198



To do list

Next progress

- 개인연구 주제 관련 Research

- 두산 관련 머신러닝 알고리즘 고도화 진행

- 갑상선 미팅 위한 준비(~ 10.20)

Sequential Music Track Skip Prediction Using Multi-branch 1D ResNet

Sanghyeong Jin

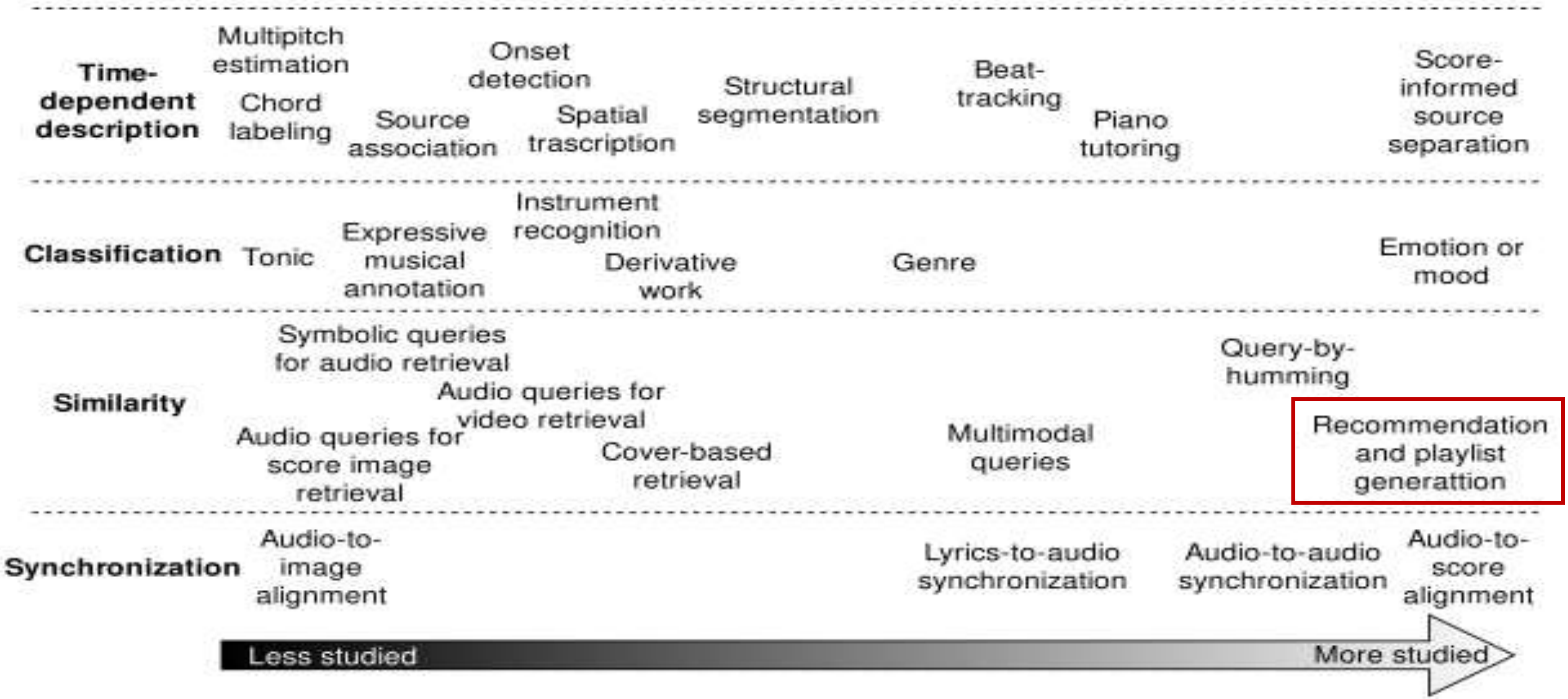
jinsanghyeong@gmail.com

2022. 10. 12.

Contents

Introduction

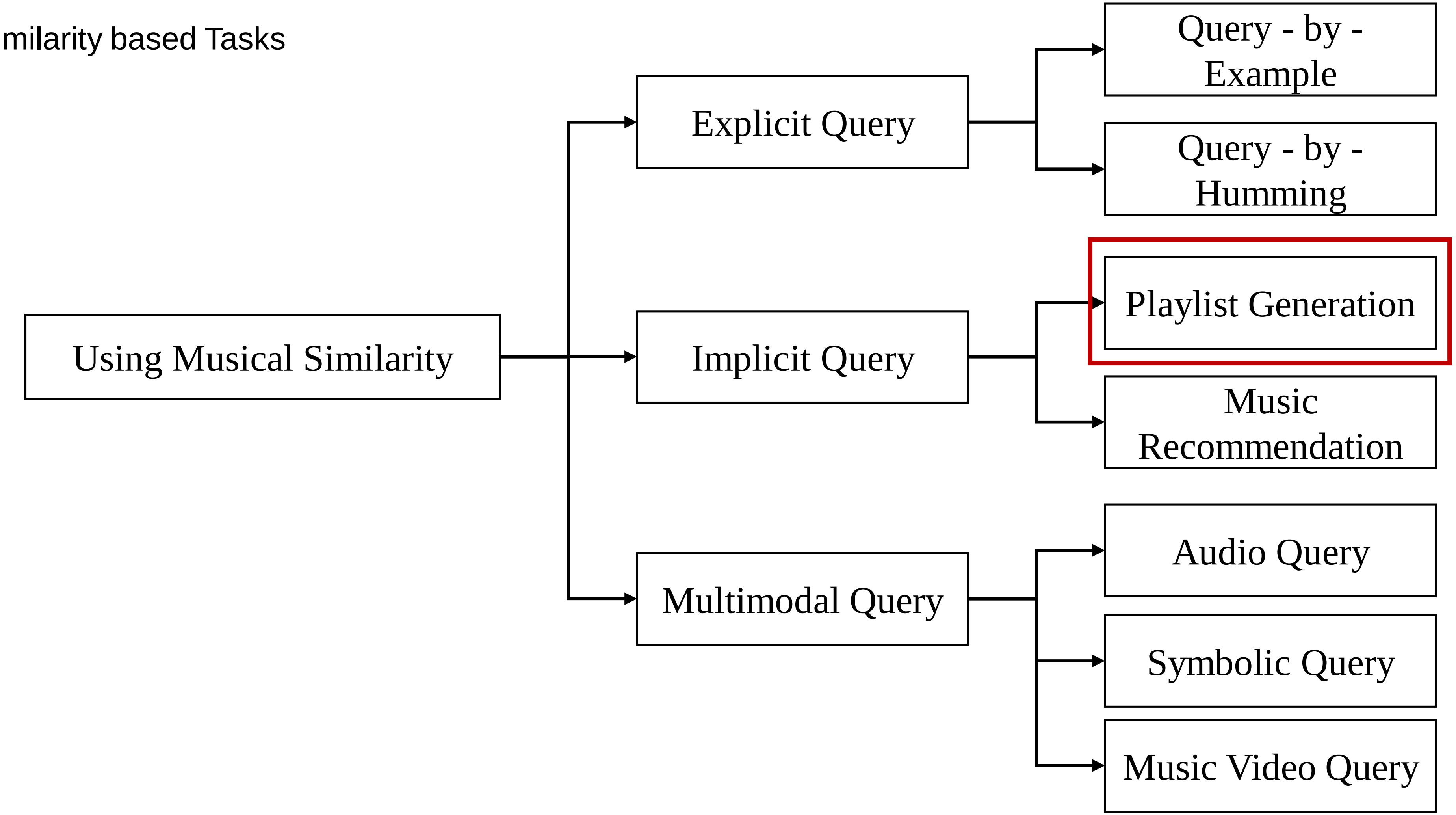
Music Information Retrieval



Introduction

Music Information Retrieval

- Musical Similarity based Tasks

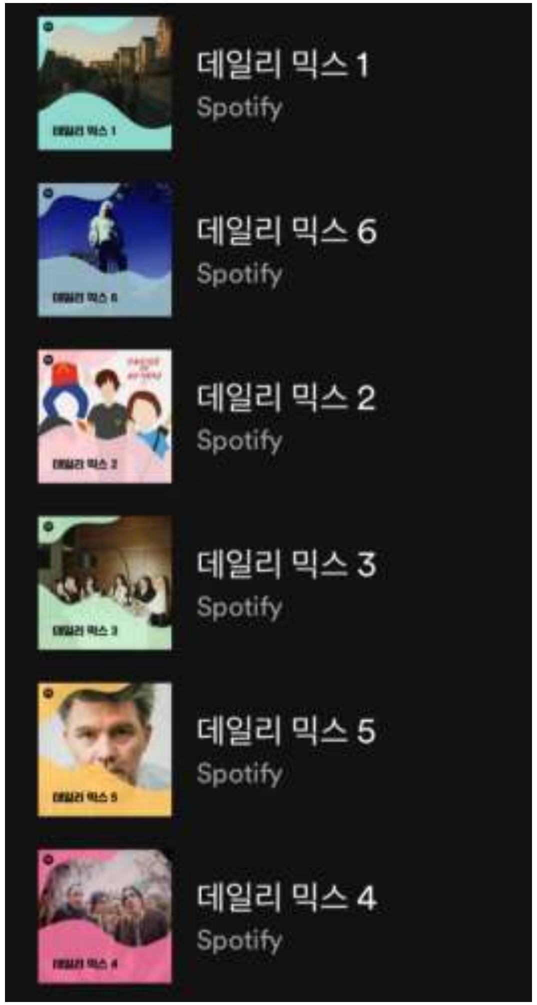


Introduction

Playlist Generation

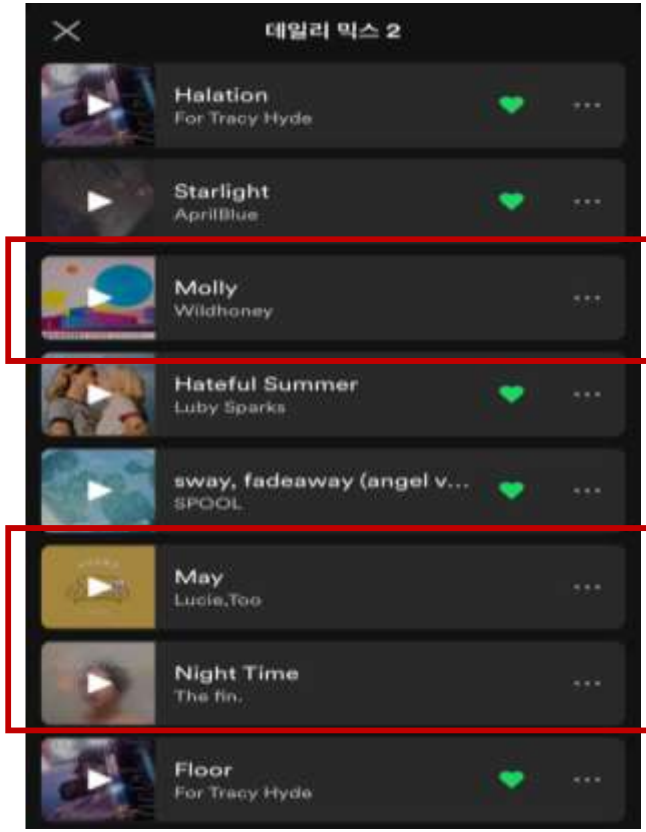
Playlist Generation

- Reinforcement Learning
- Frequent Pattern Mining
- Collaborative Filtering
- Statistical Model (Markov Model)
- ⋮



Introduction

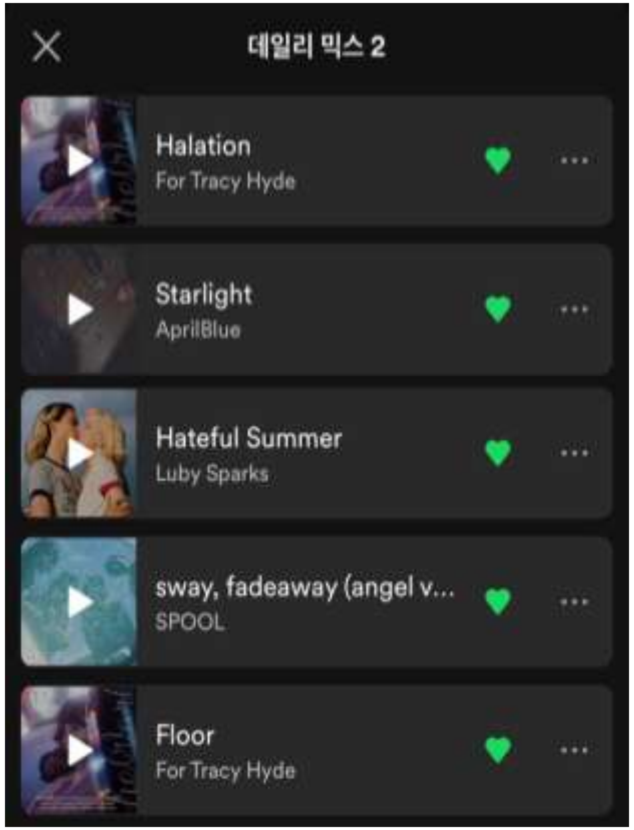
Music Track Skip Prediction



General mix playlist

Annoying to skip these tracks
at the end of each song

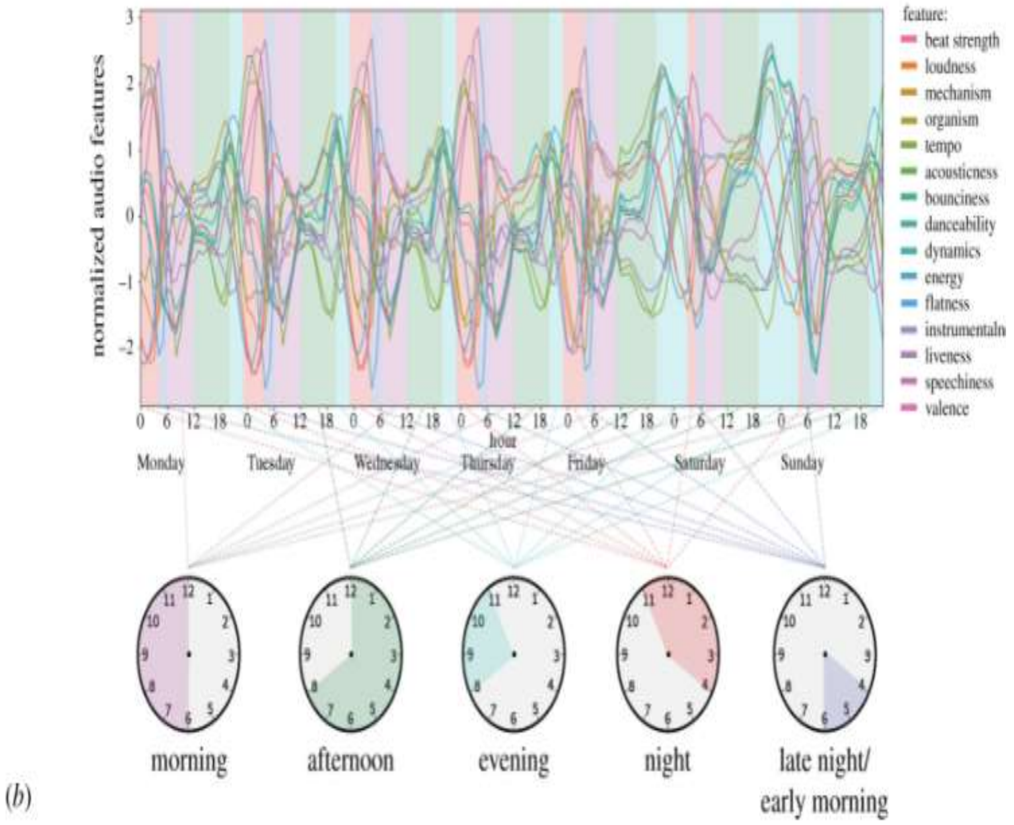
- Minimizing user skip intervention
- Smooth track sequence transition
- Generating user preferred playlist



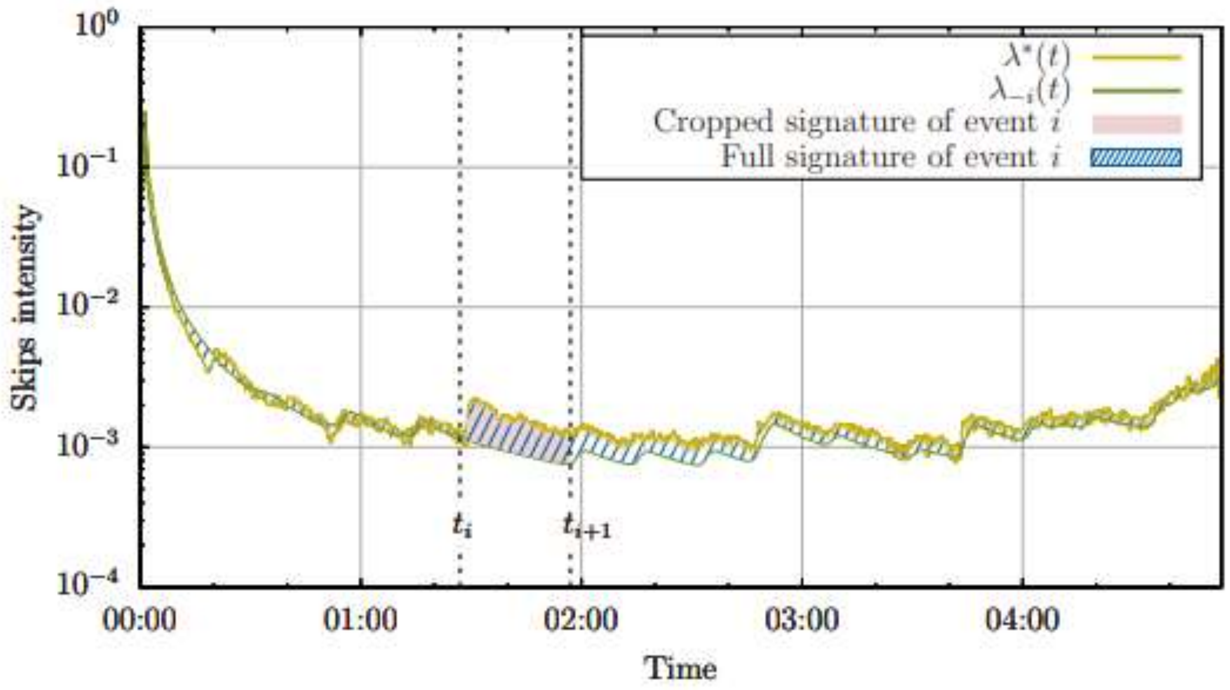
User preferred playlist

Related Work

Track Skip Behavior



Musical diurnal fluctuations

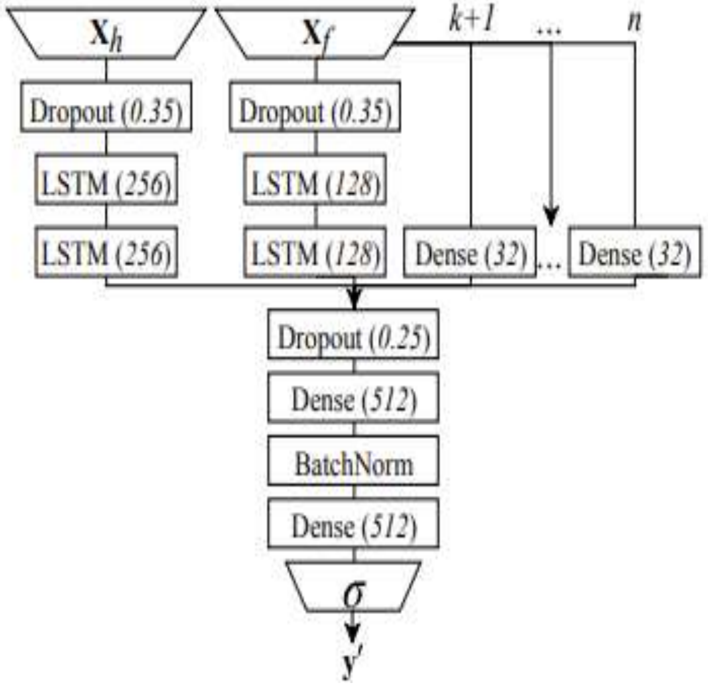


Skip rate based on time

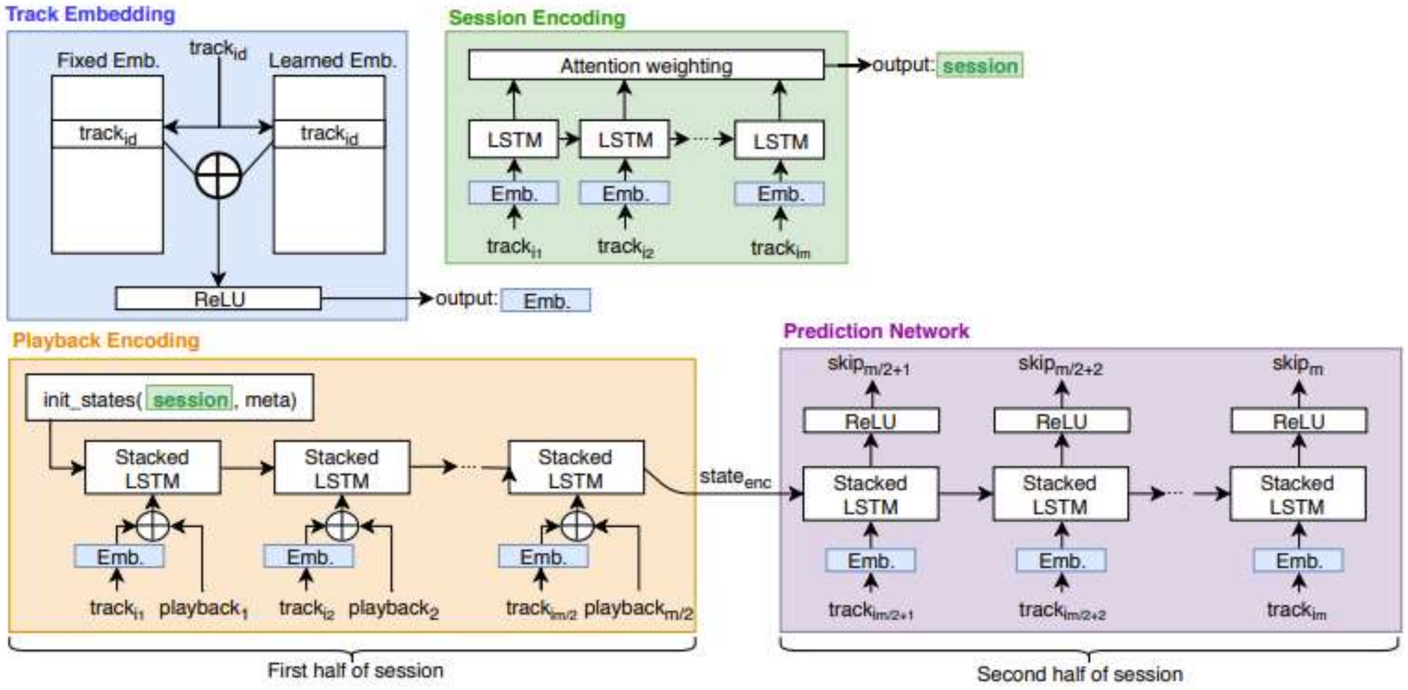
Related Work

Track Skip Prediction

- Mostly based on RNN Models



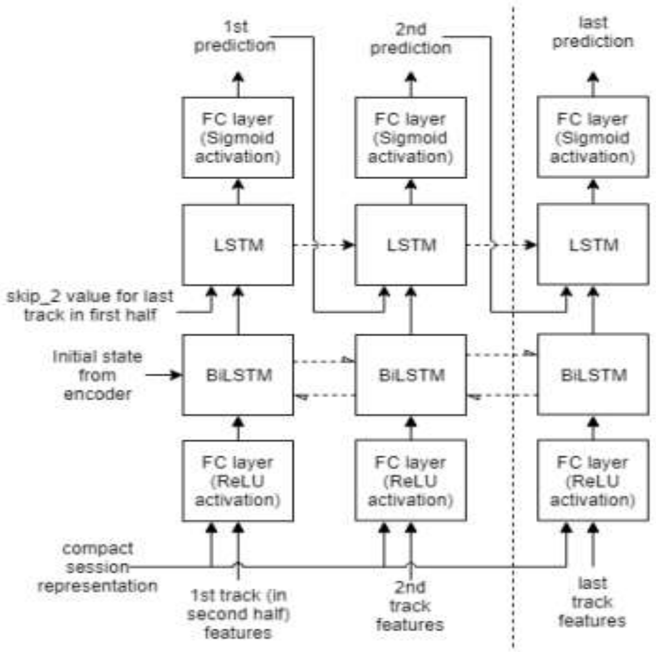
RNN-Dense



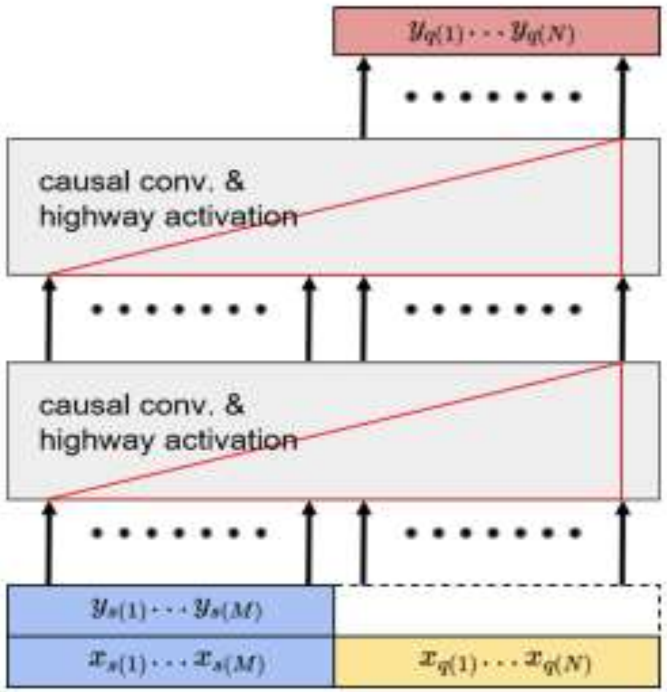
Multi-RNN

Related Work

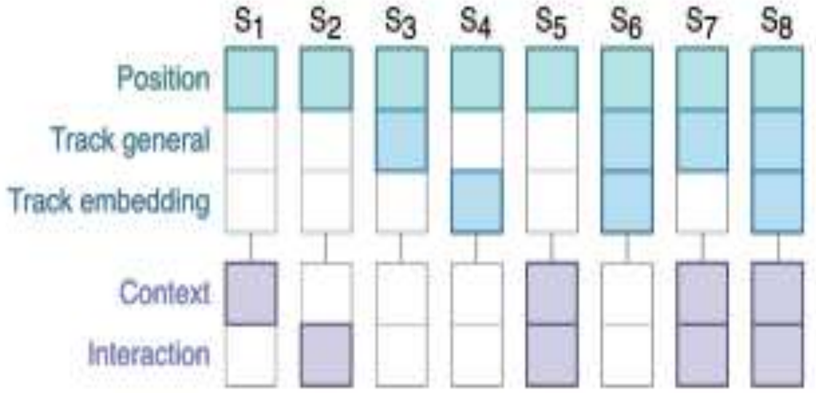
Track Skip Prediction



BiLSTM Encoder-Decoder



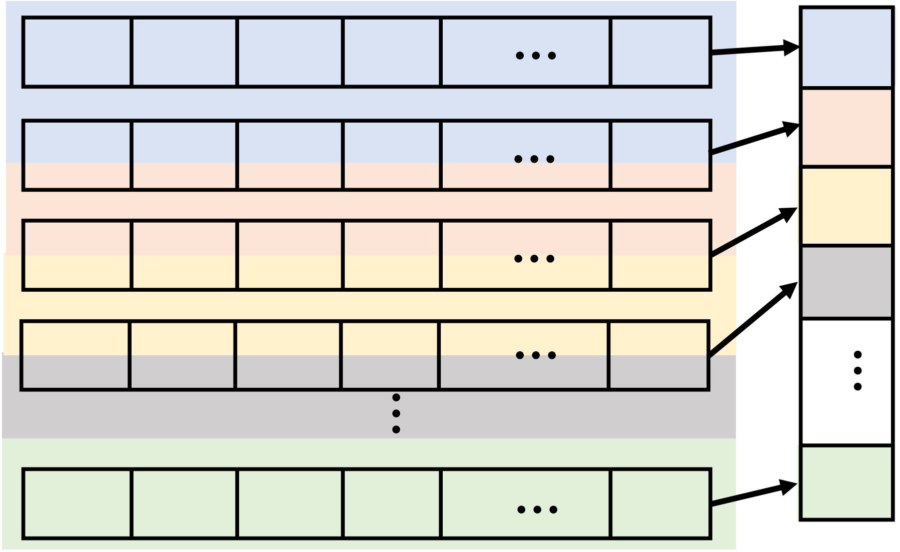
1D convolution with Highway Network



Interpretable Transformer

Related Work

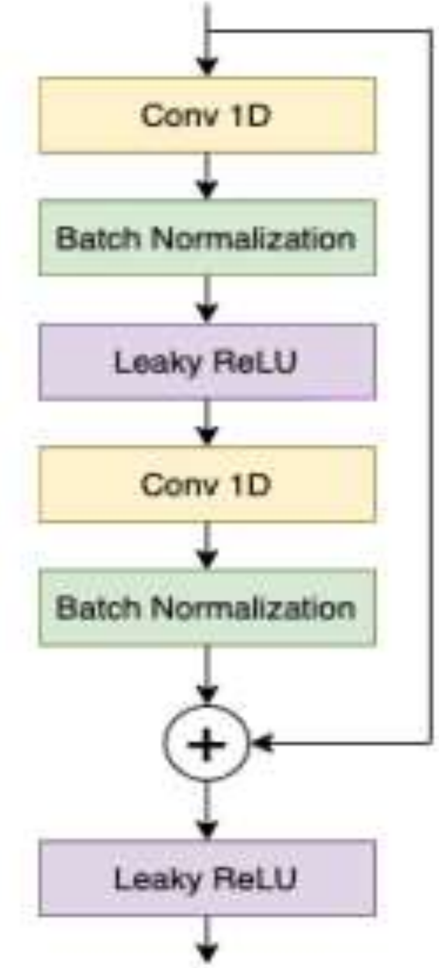
1D ResNet



1D Convolution

Variant	Functional Form
Plain	$H(\mathbf{x})$
Residual	$H(\mathbf{x}) + x$
T-Only	$H(\mathbf{x}) \cdot T(\mathbf{x}) + \mathbf{x}$
C-Only	$H(\mathbf{x}) + \mathbf{x} \cdot C(\mathbf{x})$
Coupled	$H(\mathbf{x}) \cdot T(\mathbf{x}) + \mathbf{x} \cdot (1 - T(\mathbf{x}))$
Full	$H(\mathbf{x}) \cdot T(\mathbf{x}) + \mathbf{x} \cdot C(\mathbf{x})$

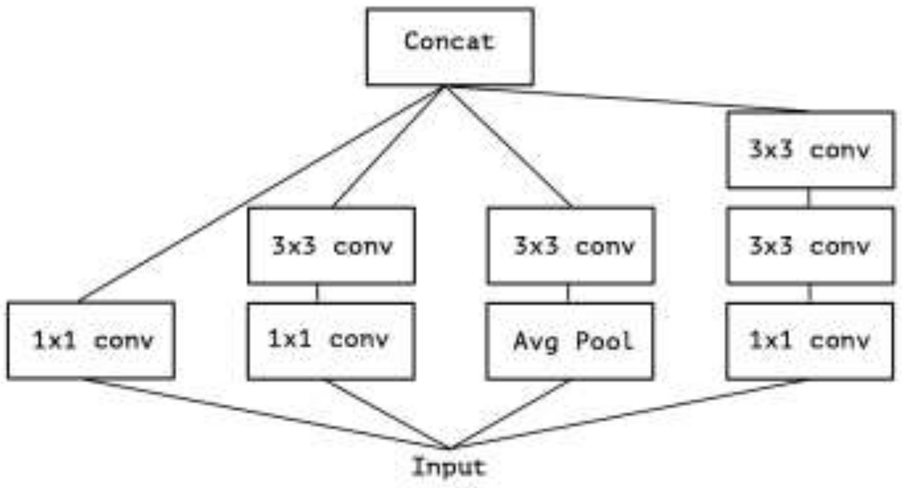
Residual Connection



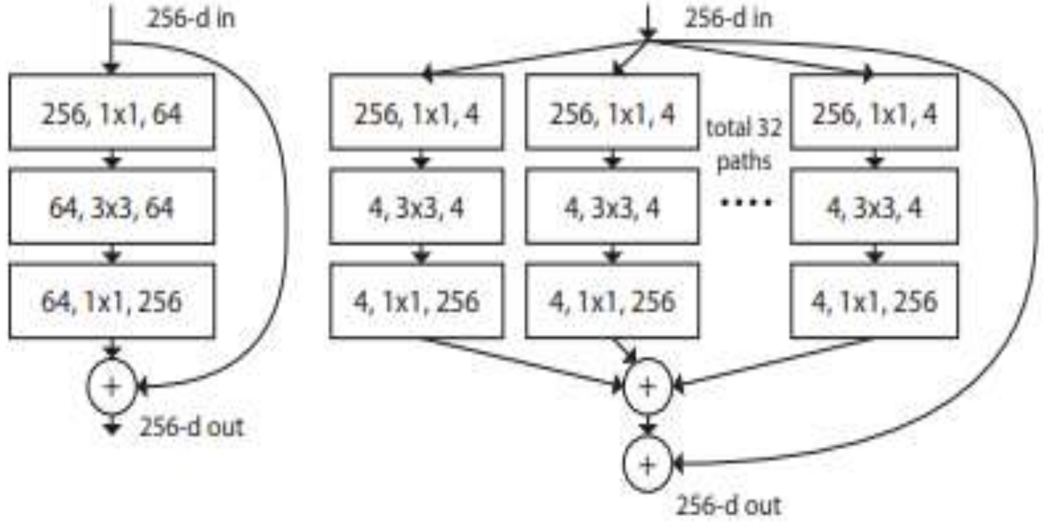
1D Residual Block

Related Work

Multi-branch Convolution



Inception V3



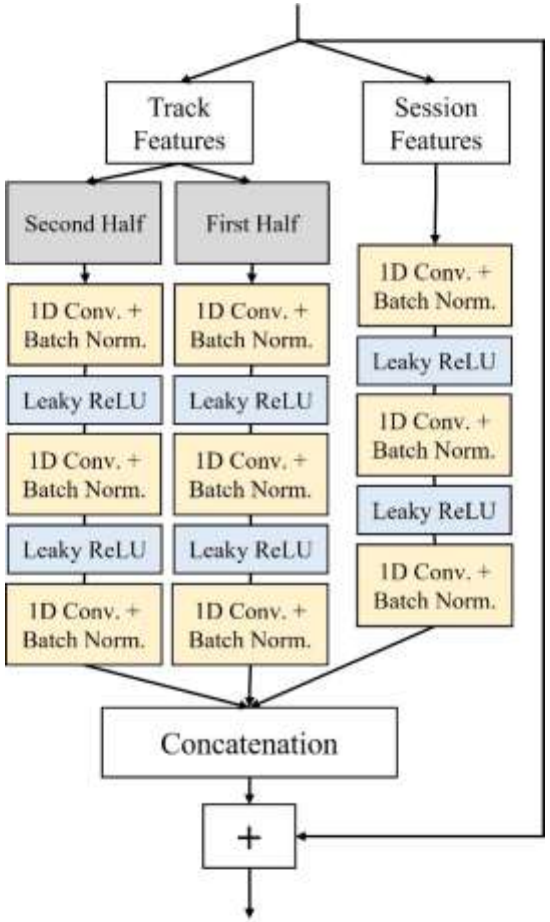
ResNeXt

Proposed Method

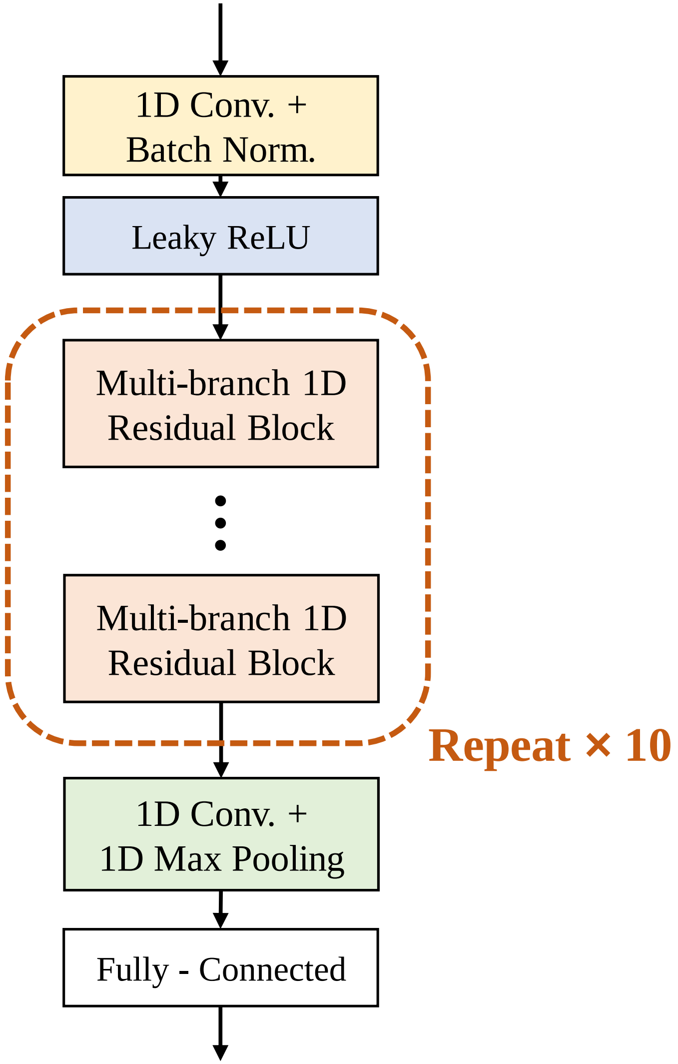
Multi-branch 1D Residual Block

B × (S + T) × L		
Track Features		Session Features
B × T × L		B × S × L
Second Half	First Half	
B × T × L/2	B × T × L/2	B × S × L
B × T/2 × L/2	B × T/2 × L/2	B × S/2 × L
B × T × L/2	B × T × L/2	B × T × L
Concatenation		
B × (S + T) × L		

B : Batch size, S : Session size, T : Track size
L : Sequence Length



Multi-branch 1D ResNet



Experimental Settings

MAA (Mean Average Accuracy)

$$AA = \frac{\Sigma_{i=1}^{T} A(i)L(i)}{T}$$

T : Number of tracks to be predicted
A(i) : Accuracy to the *i*-th track in sequence
L(i) : Boolean indicator that if *i*-th prediction was correct (0, 1)

Ground Truth	Predicted	AA (Average Accuracy)
1, 1, 1, 1, 1	1, 1, 1, 1, 0	0.800
1, 1, 1, 1, 1	1, 1, 1, 0, 1	0.760
1, 1, 1, 1, 1	1, 1, 0, 1, 1	0.710
1, 1, 1, 1, 1	1, 0, 1, 1, 1	0.643
1, 1, 1, 1, 1	0, 1, 1, 1, 1	0.543

$$\frac{\left(\frac{1}{1} * 1 + \frac{2}{2} * 1 + \frac{3}{3} * 1 + \frac{4}{4} * 1 + \frac{4}{5} * 0\right)}{5} = 0.800$$

$$\frac{\left(\frac{1}{1} * 1 + \frac{2}{2} * 1 + \frac{2}{3} * 0 + \frac{3}{4} * 1 + \frac{4}{5} * 1\right)}{5} = 0.710$$

$$\frac{\left(\frac{0}{1} * 0 + \frac{1}{2} * 1 + \frac{2}{3} * 1 + \frac{3}{4} * 1 + \frac{4}{5} * 1\right)}{5} = 0.543$$

Experimental Settings

- Datasets
  - Music Streaming Sessions Dataset (MSSD)
  - Number of Samples: 167,880 session histories (10,000 unique session)
  - Number of Classes: 2 (Skip / Not Skip)
  - Input : (74, 20) - (Session & Track Features, Sequence Length) / Sequence that less than 20 includes zero padding
  - Output : (10, 1) - Prediction probability for the 10 tracks in second half
- Cross-Validation for Test Performance
  - 10 iterations / Group K-Fold (by Session id)
  - Data Split Ratio: (Train : Test) = (0.9: 0.1)
- Hyper Parameter Setting:

<table>
<tr><th>Model</th><th>Batch Size</th><th>Epochs</th><th>Loss Function</th><th>Optimizer</th><th>LR</th></tr>
<tr><td>Proposed</td><td rowspan="5">16</td><td rowspan="5">10</td><td rowspan="5">Binary Cross Entropy</td><td rowspan="2">Adam</td><td rowspan="3">1e-4</td></tr>
<tr><td>Highway 1D Conv.</td></tr>
<tr><td>Encoder-Decoder</td><td>RMSprop</td></tr>
<tr><td>Multi-RNN</td><td rowspan="2">Adam</td><td>1e-3</td></tr>
<tr><td>RNN-Dense</td><td>1e-4</td></tr>
</table>

Experimental Results

t-test Result

Model	MAA Mean ± Standard Deviation	Average Rank
Proposed	**0.6879 ± 0.0371**	**1.47**
Highway 1D Conv. [12]	0.5976 ± 0.0885 ▼	3.23
Encoder-Decoder [16]	0.5462 ± 0.1093 ▼	3.83
Multi-RNN [14]	0.6082 ± 0.0768 ▼	2.93
RNN-Dense [15]	0.5740 ± 0.0901 ▼	3.53

▼ indicates corresponding model is significantly worse than proposed model at significance level α=0.05

Experimental Results

Friedman-test Result

	Statistics	p-value
Proposed	40.667	3.15e-08

significance level α=0.05

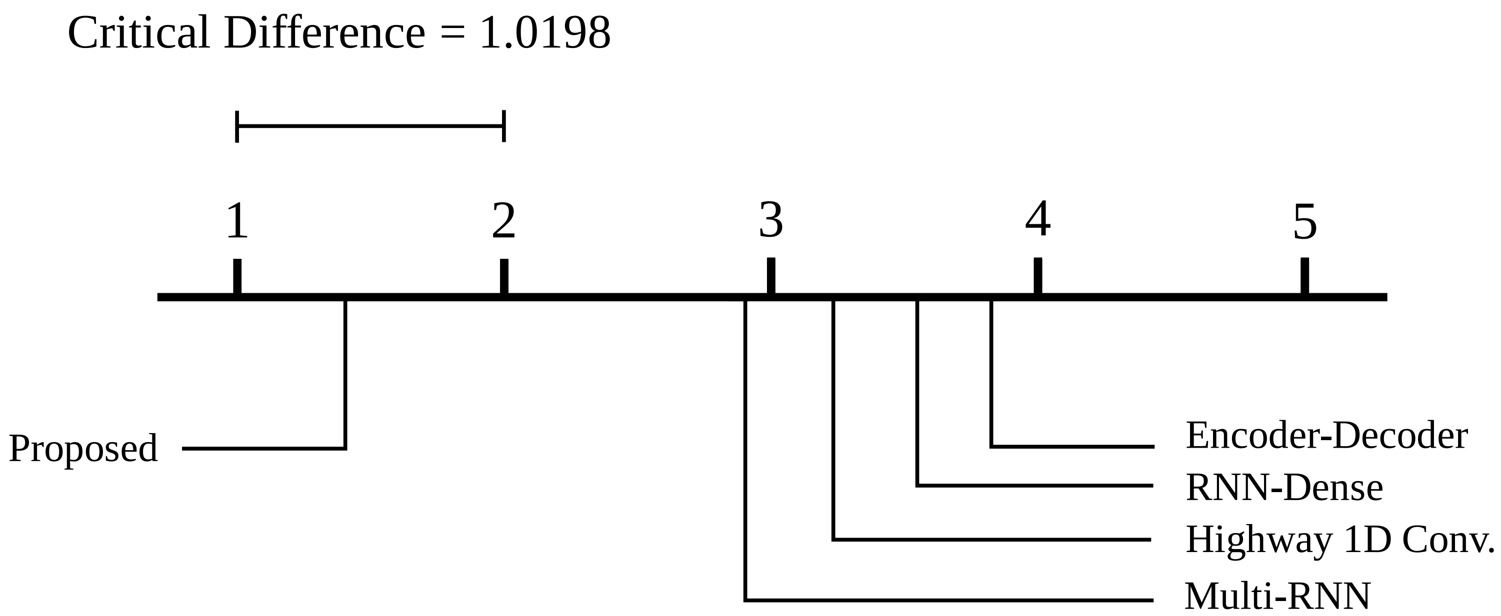
Wilcoxon signed-rank test Result

	Comparison models			
	Highway 1D Conv. [12]	Encoder-Decoder [16]	Multi-RNN [14]	RNN-Dense [15]
Proposed ***versus*** (p-value)	Win (8.19e-05)	Win (1.97e-05)	Win (2.84e-05)	Win (2.16e-5)

significance level α=0.05

Experimental Results

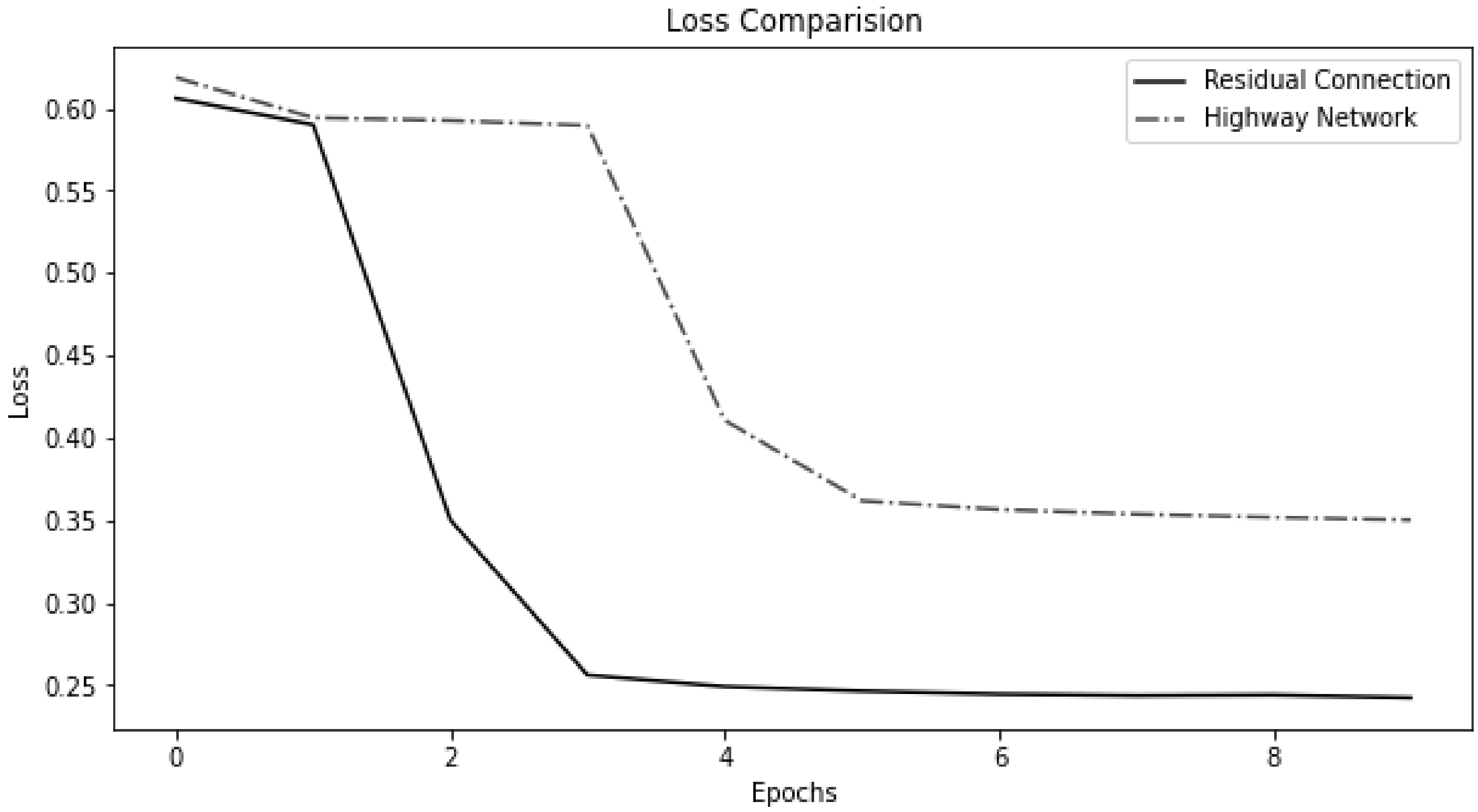
Bonferroni-Dunn test Result



Experimental Results

Discussion

- Highway Network vs. Residual Connection



Experimental Results

Discussion

- Visualization 1D CNN Filter

Basic 1D ResNet

Proposed (Multi-branch 1D ResNet)

Conclusion

Summary

- Proposed multi-branch 1D residual block based on 1D convolution and 1D ResNet

- Proposed method perform significantly better than conventional RNN-based models

- Explicitly split multi-branch convolution can drive high-correlated feature learning

Future Works

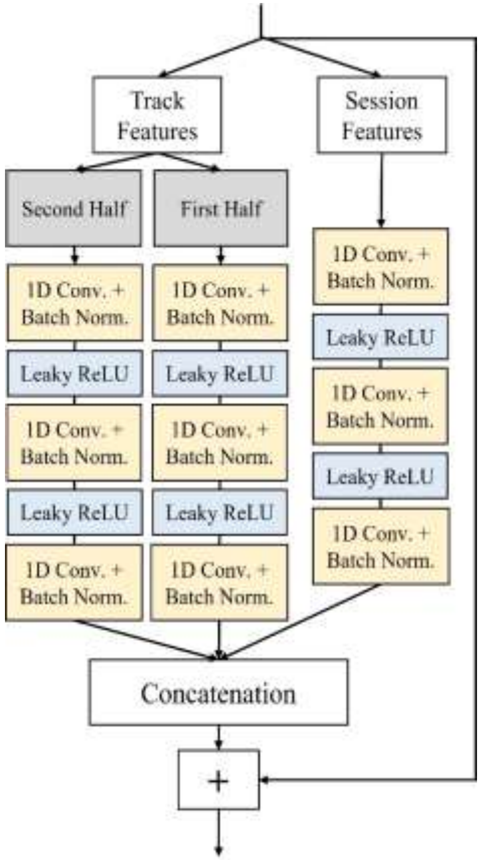
- Using track more audio features

- Applying grouped convolution (separate inputs into same sizes)

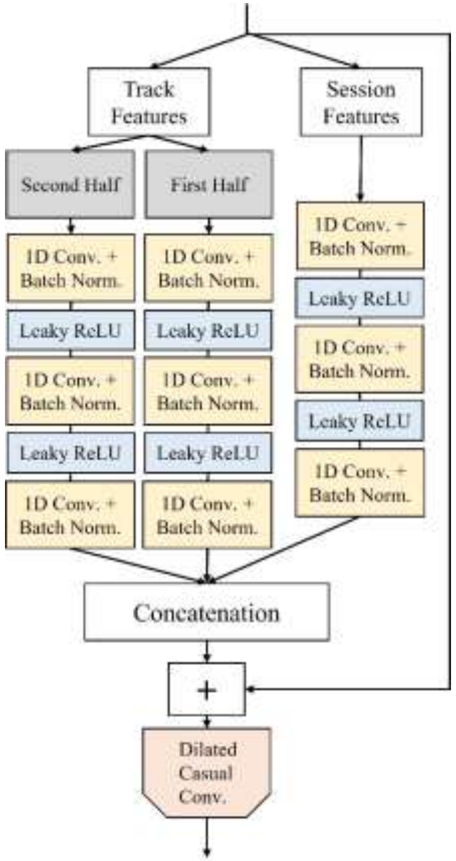
Appendix

1D ResNet Variation Comparison

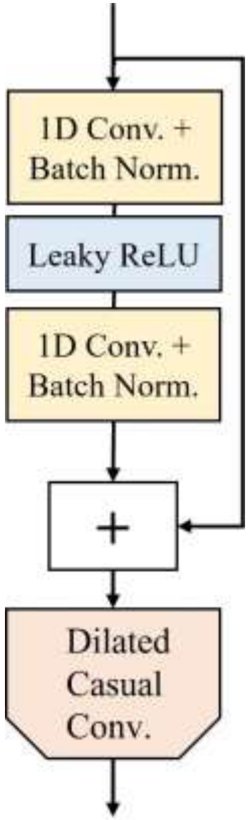
* DCC : Dilated Casual Convolution



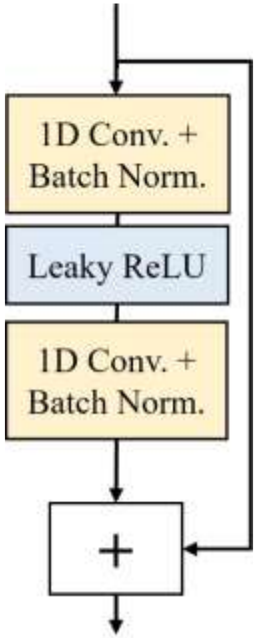
1. Proposed



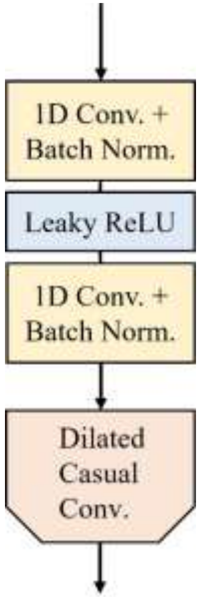
2. Multi-branch 1D ResNet + DCC



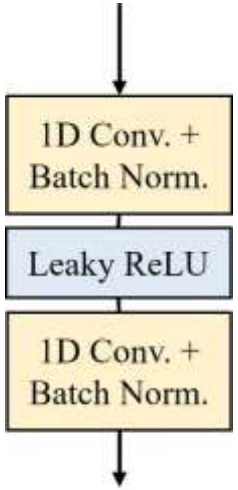
3. Basic 1D ResNet + DCC



4. Basic 1D ResNet



5. Residual Conn. Removed + DCC



6. Residual Conn. Removed

Appendix

t-test Result

Model	MAA Mean ± Standard Deviation	Average Rank
Proposed	**0.6879 ± 0.0371**	**1.57**
Multi-Branch 1D ResNet + DCC	0.6829 ± 0.0431	1.5
Basic 1D ResNet + DCC	0.4468 ± 0.1035 ▼	4.3
Basic 1D ResNet	0.4149 ± 0.0380 ▼	4.32
Residual Conn. Removed + DCC	0.4006 ± 0.0318 ▼	4.8
Residual Conn. Removed	0.4066 ± 0.0225 ▼	4.52

▼ indicates corresponding model is significantly worse than proposed model at significance level α=0.05
* DCC : Dilated Casual Convolution

Appendix

Friedman-test Result

	Statistics	p-value
Proposed	103.030	1.21e-20

significance level α=0.05

Wilcoxon signed-rank test Result

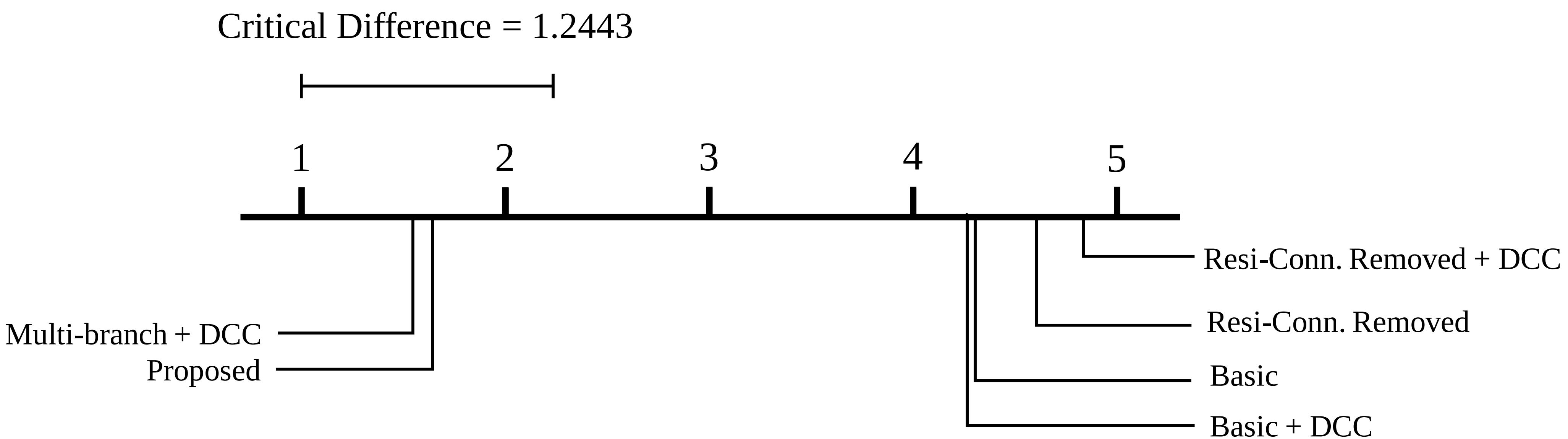
* DCC : Dilated Casual Convolution

	Comparison models				
	Multi-Branch 1D ResNet + DCC	Basic 1D ResNet + DCC	Basic 1D ResNet	Residual Conn. Removed + DCC	Residual Conn. Removed
Proposed ***versus*** (p-value)	Tie (0.7813)	Win (2.35e-06)	Win (1.73e-06)	Win (1.73e-06)	Win (1.73e-06)

significance level α=0.05

Appendix

Bonferroni-Dunn test Result



* DCC : Dilated Casual Convolution

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[14]] A. Oord, S. Dieleman, H. Zen, et al. “Wavenet: A generative model for raw audio”. arXiv:1609.03499, 2016.

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To Do List

- Get 1D feature maps

- Analysis 1D feature maps

Neural Collaborative Filtering Recommendation System Paper Review

ChaeLyn Lee

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12th Oct, 2022

To Do List from Previous Seminar

- Review of 25 papers
- Experiment with the data in the paper

Proposed Method

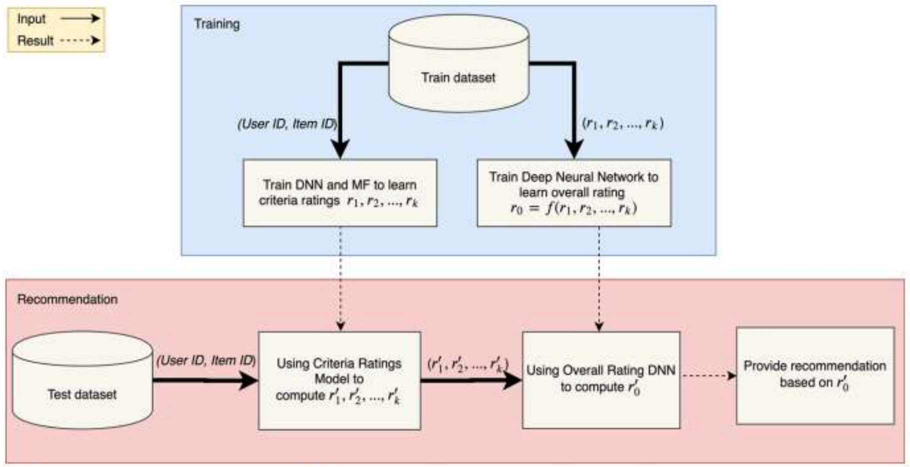


Fig. 1 The framework of the proposed model, including two steps: the Training and the Recommendation step

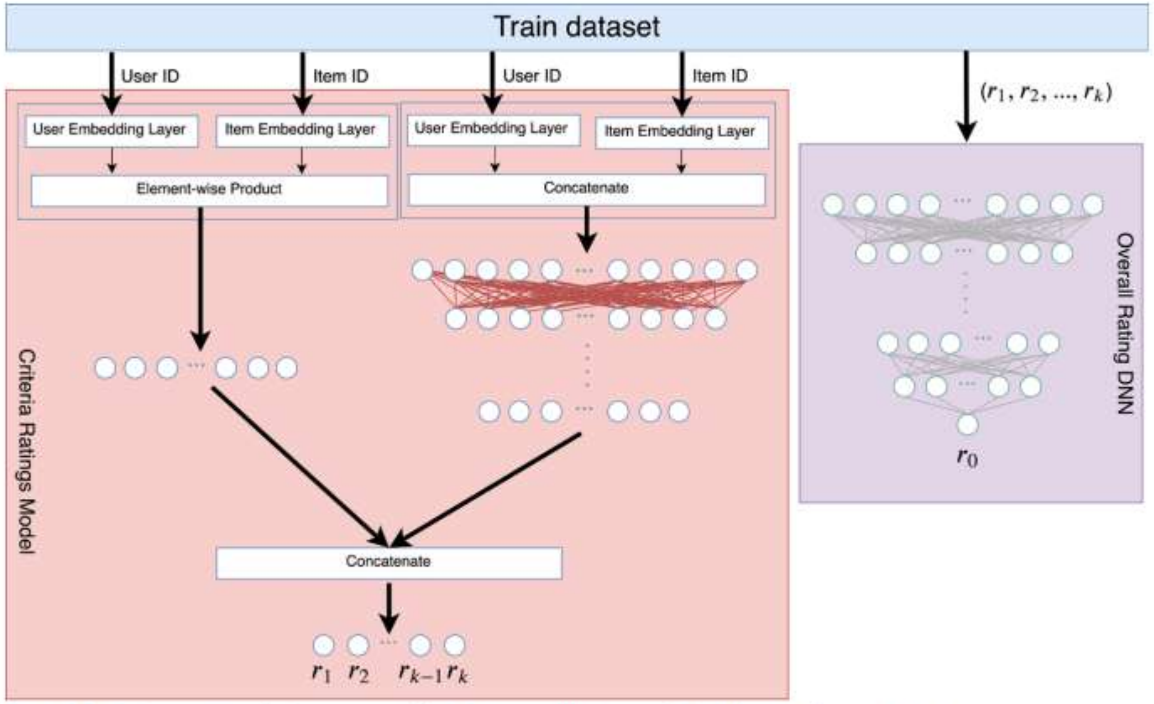


Fig. 2 The architecture of the two models: Criteria Ratings Model and Overall Rating DNN

Proposed model : **MCRS(Multi-Criteria Recommender System)**

- Recommendation system that combines DNN and MF
- Step

1. Data from users and items are input to a model that combines DNN and MF to predict the reference rating
2. Use DNN to predict overall ratings

Multi-criteria collaborative filtering recommender by fusing deep neural network and matrix factorization(Journal of Big Data, 2020)

Experimental Settings

Table 1 TripAdvisor dataset statistics

Field description	Value
Number of users	72,119
Number of hotels	1850
Number of ratings	81,085
Data sparsity	99.94%

Table 3 Movies dataset statistics

Field description	Value
Number of users	6078
Number of movies	976
Number of ratings	62,156
Data sparsity	98.95%

Multi-criteria collaborative filtering recommender by fusing deep neural network and matrix factorization(Journal of Big Data, 2020)

Experimental Results

Table 6 Evaluation results

Dataset	Metric	SVD	SVD++	SlopeOne	Baseline estimates	Single DNN	DMCCF [19]	Our
TripAdvisor	*MAE*	0.8071 ± 0.0043	0.8222 ± 0.0071	0.9160 ± 0.0053	0.8094 ± 0.0019	0.7855 ± 0.0153	0.7552 ± 0.0050	0.7434 ± 0.0068
	F_1	0.8370 ± 0.0035	0.8390 ± 0.0035	0.8666 ± 0.0018	0.8391 ± 0.0020	0.8572 ± 0.0024	0.8769 ± 0.0043	0.8811 ± 0.0031
	F_2	0.7951 ± 0.0031	0.7991 ± 0.0057	0.9248 ± 0.0011	0.7986 ± 0.0029	0.9176 ± 0.0057	0.9295 ± 0.0014	0.9319 ± 0.0204
	FCP	0.5024 ± 0.0210	0.5092 ± 0.0056	0.5096 ± 0.0661	0.5025 ± 0.0117	0.4957 ± 0.0102	0.5126 ± 0.0160	0.5164 ± 0.0048
	MAP	0.3935 ± 0.0057	0.3483 ± 0.0049	0.3006 ± 0.0026	0.3881 ± 0.0023	0.4481 ± 0.0091	0.4643 ± 0.0072	0.4836 ± 0.0047
	MRR	0.7272 ± 0.0054	0.7513 ± 0.0018	0.7502 ± 0.0037	0.7374 ± 0.0028	0.7244 ± 0.0092	0.7664 ± 0.0039	0.7693 ± 0.0036
Movies dataset	*MAE*	2.1072 ± 0.0168	2.1594 ± 0.0050	2.1798 ± 0.0112	2.1333 ± 0.0069	2.0613 ± 0.0347	2.0474 ± 0.0119	2.0188 ± 0.0181
	F_1	0.8061 ± 0.0049	0.7985 ± 0.0010	0.7860 ± 0.0026	0.8107 ± 0.0031	0.8344 ± 0.0106	0.8414 ± 0.0041	0.8563 ± 0.0036
	F_2	0.7608 ± 0.0062	0.7553 ± 0.0023	0.7325 ± 0.0045	0.7699 ± 0.0045	0.8256 ± 0.0287	0.8383 ± 0.0049	0.8442 ± 0.0056
	FCP	0.6022 ± 0.0107	0.5985 ± 0.0029	0.6251 ± 0.0098	0.6233 ± 0.0027	0.6226 ± 0.0055	0.6258 ± 0.0083	0.6289 ± 0.0029
	MAP	0.1910 ± 0.0056	0.2144 ± 0.0035	0.2089 ± 0.0067	0.1612 ± 0.0027	0.2136 ± 0.0143	0.2345 ± 0.0109	0.2458 ± 0.0090
	MRR	0.6651 ± 0.0091	0.6502 ± 0.0048	0.6085 ± 0.0048	0.6721 ± 0.0052	0.6922 ± 0.0145	0.7061 ± 0.0078	0.7092 ± 0.0049

Multi-criteria collaborative filtering recommender by fusing deep neural network and matrix factorization(Journal of Big Data, 2020)

Proposed Method

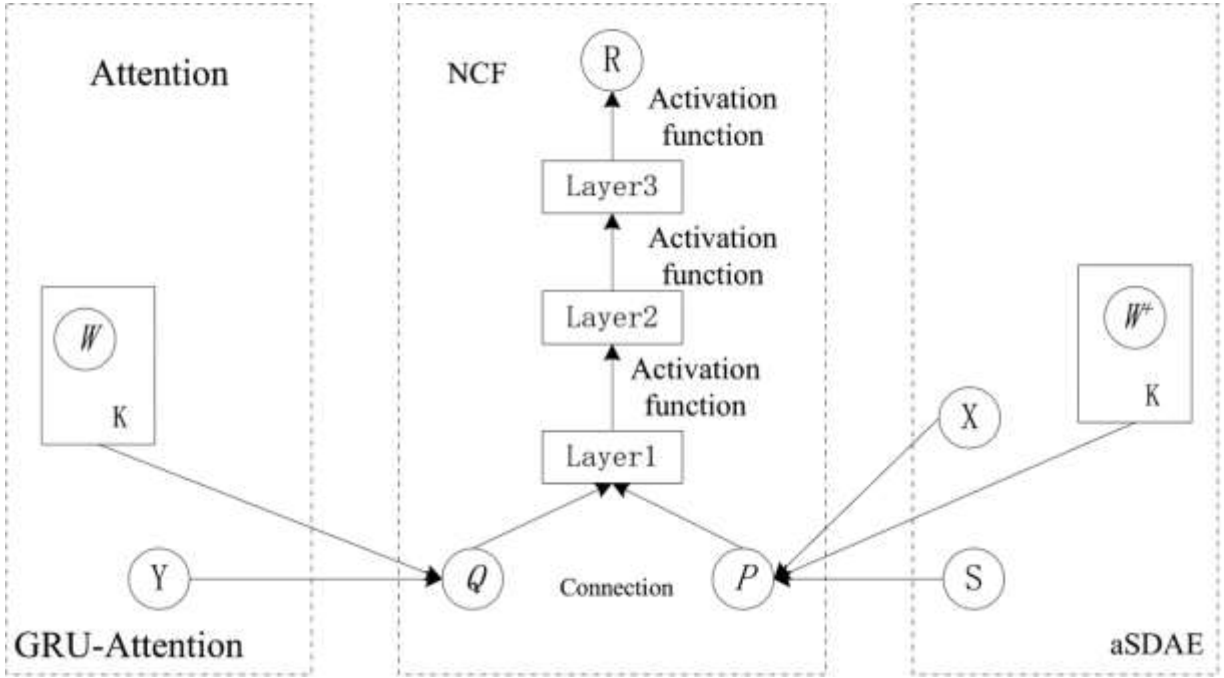
R : user-item rating matrix

X,Y : user and item auxiliary information

S : user rating information

W^{+}, W : weight parameters of aSDAE and GRU-Attention

K : latent vector dimension

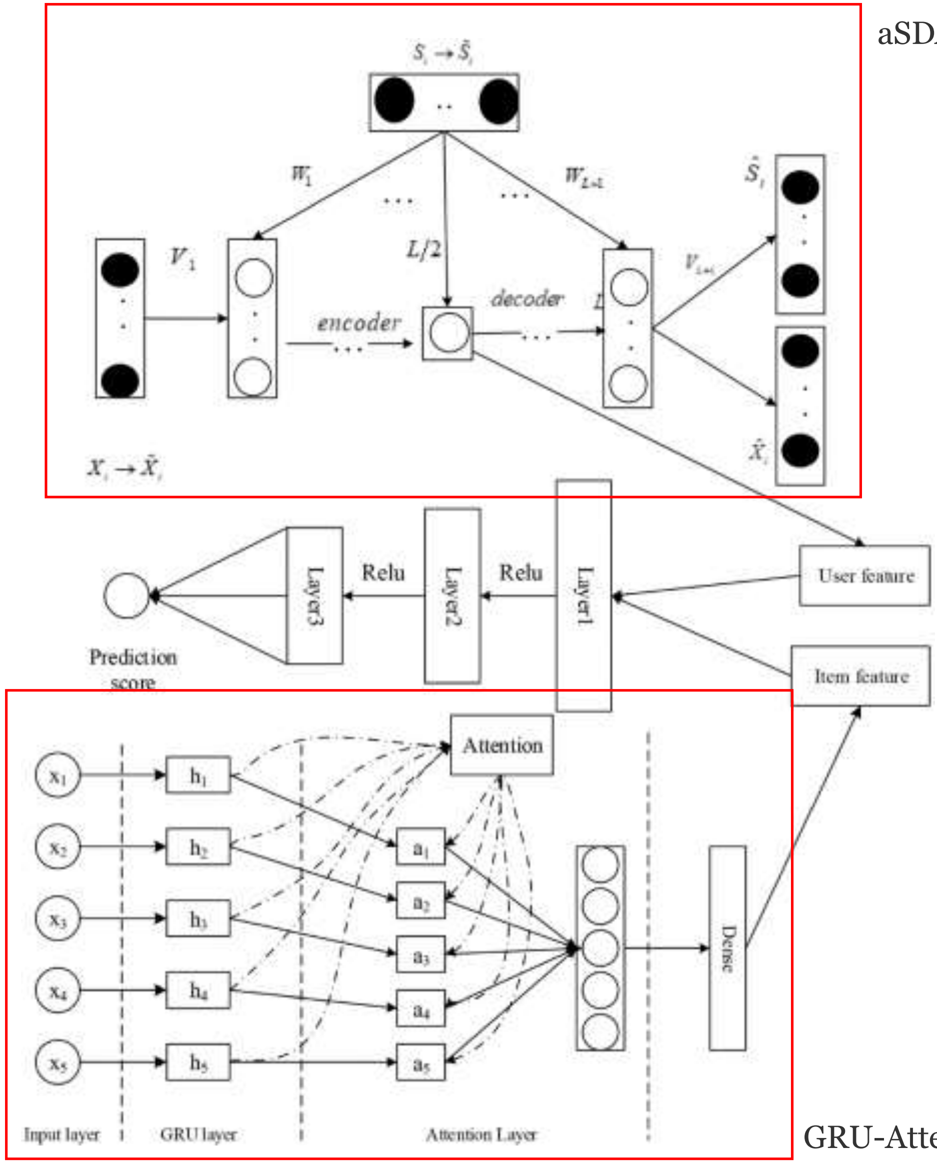


Proposed model : **GANCF(GRU_Attention Neural collaborative filtering)**

(GRU is a type of RNN framework with a gate mechanism, Inspired by LSTM)

Attention neural collaboration filtering based on GRU for recommender systems(Complex & Intelligent Systems, 2021)

Proposed Method



aSDAE(additional Stacked Denoising Autoencoder) model

GRU-Attention model

The overall flow diagram of the GANCF

Attention neural collaboration filtering based on GRU for recommender systems(Complex & Intelligent Systems, 2021)

Experimental Results

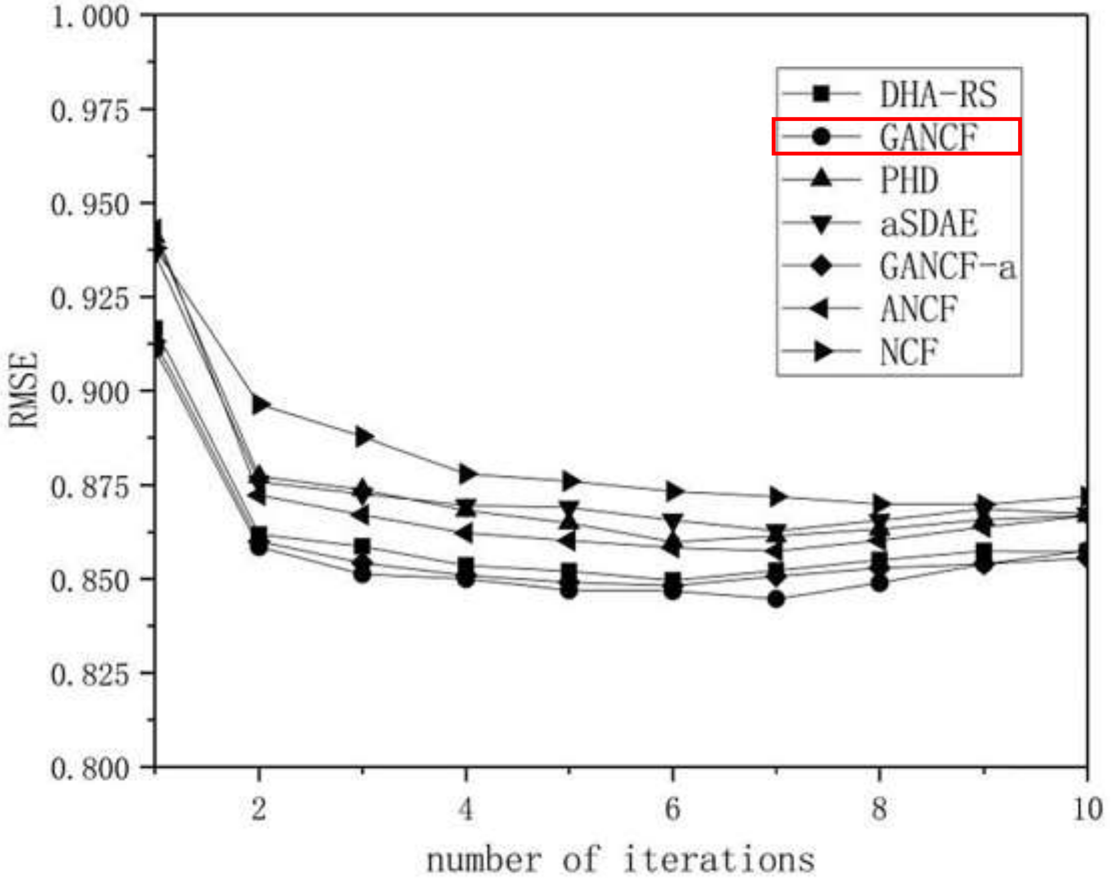


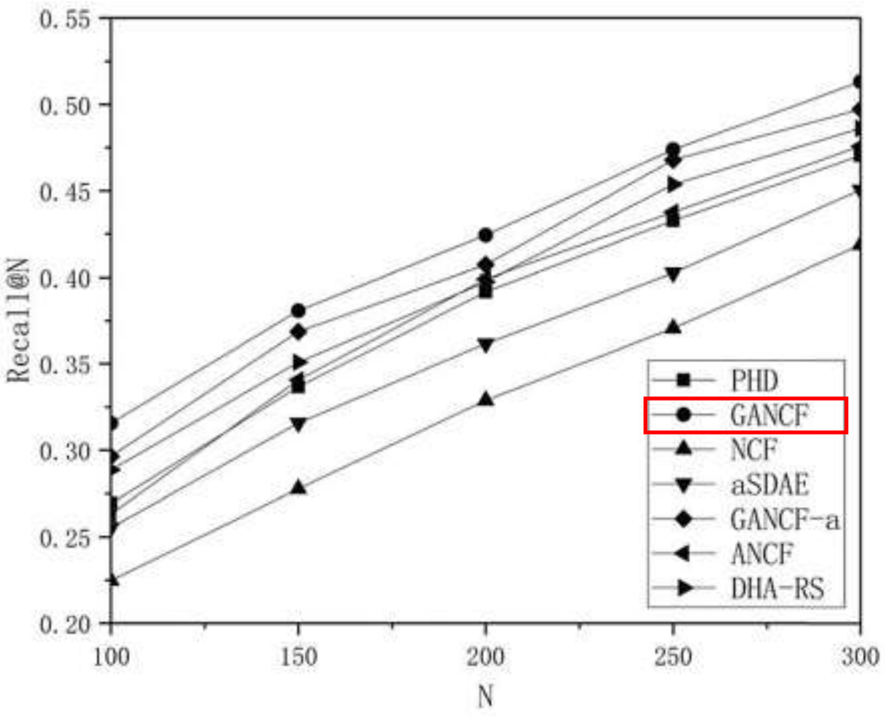
Table 1 MovieLens statistics

Dataset	Number of users	Number of items	Sparsity (%)
ML-100 K	943	1682	93.76
ML-1 M	6040	3706	95.53

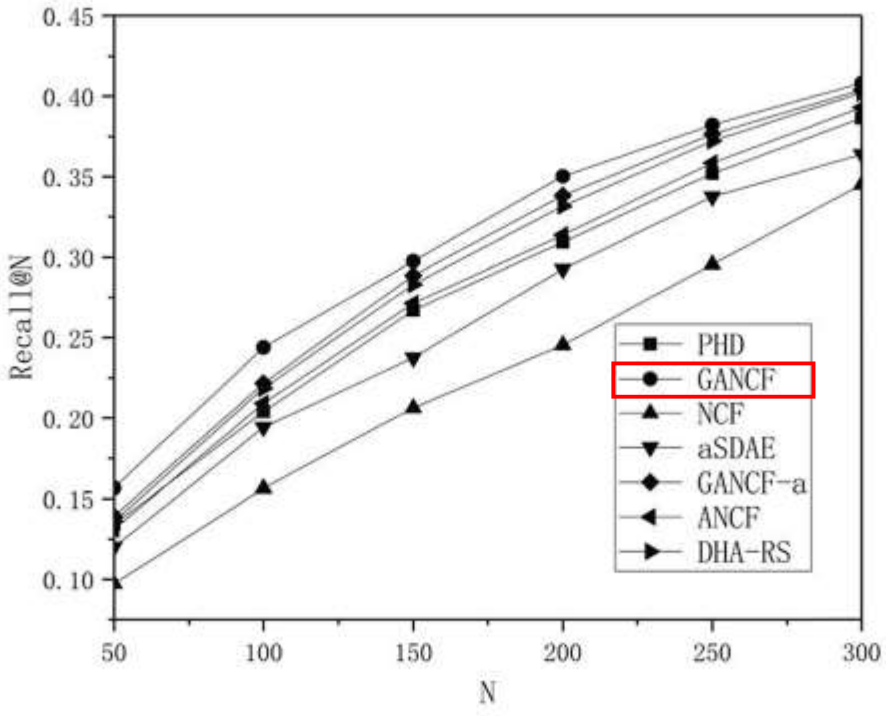
Model	RMSE
NCF	0.87735
ANCF	0.85447
aSDAE	0.86283
PHD	0.85914
DHA-RS	0.85075
GANCF-a	0.84862
GANCF	0.84471

Attention neural collaboration filtering based on GRU for recommender systems(Complex & Intelligent Systems, 2021)

Experimental Results



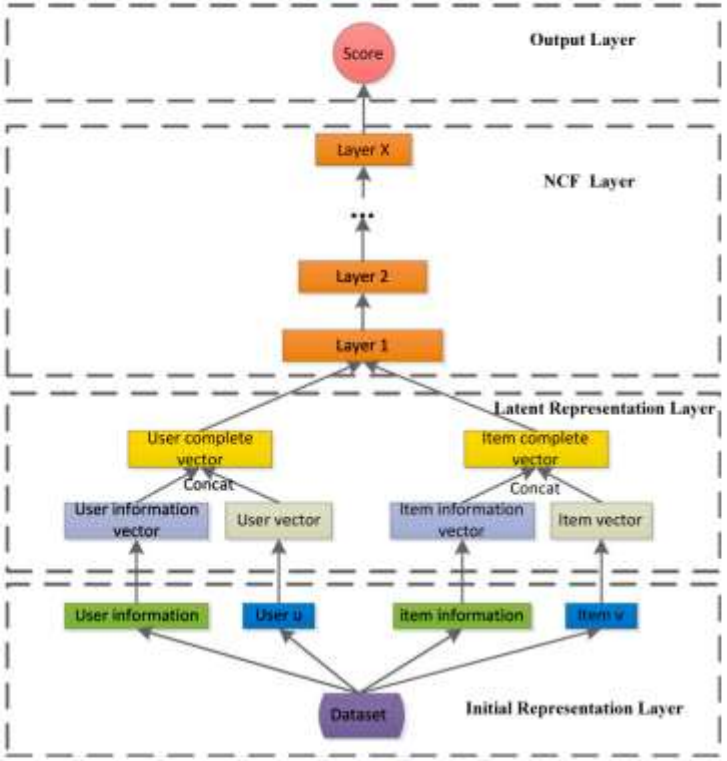
(1) ml-100k



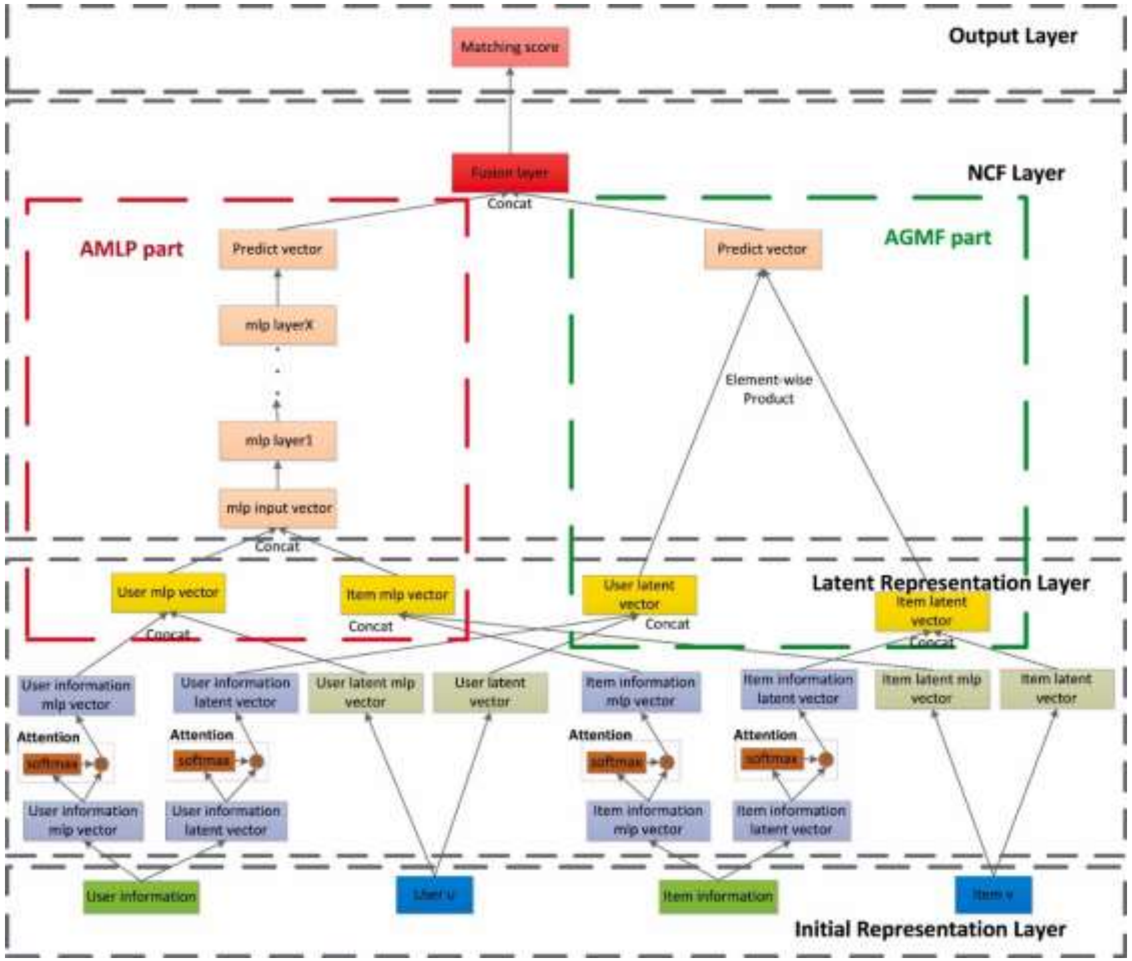
(2) ml-1m

Attention neural collaboration filtering based on GRU for recommender systems(Complex & Intelligent Systems, 2021)

Proposed Method



ANCF(Attribute-based Neural Collaborative Filtering)



Proposed model : ANeuMF(Attribute-based neural matrix factorization)

Purpose : Flexible and effective learning of low-dimensional linear relationships and high-dimensional nonlinear relationships between user items.

Attribute-based neural collaborative filtering(Expert Systems with Applications, 2020)

Experimental Results

Table 1
Statistics of the datasets.

Statistics	MovieLens 100k	MovieLens 1M	Ta-Feng	Book-Crossing
# of Users	944	6040	32 266	7255
# of Items	1683	3952	23 812	25 520
# of Ratings	100 000	1 000 209	817 741	306 220
Rating density	0.06294	0.04190	0.00106	0.00165

Table 3
Comparison results of different methods in terms of NDCG@10 an HR@10.

Algorithms	MovieLens 100k			MovieLens 1M			Ta-Feng			Book-Crossing		
	HR@10	NDCG@10	Recall@10	HR@10	NDCG@10	Recall@10	HR@10	NDCG@10	Recall@10	HR@10	NDCG@10	Recall@10
MF	0.8208	0.5572	0.7943	0.6983	0.4196	0.6750	0.6017	0.3891	0.5903	0.4232	0.2453	0.4021
NCF	0.8399	0.5692	0.8144	0.7310	0.4475	0.7126	0.6661	0.4458	0.6376	0.4790	0.2891	0.4496
DeepCF	0.8526	0.5959	0.8218	0.7346	0.4593	0.7162	0.6561	0.4341	0.6245	0.4873	0.2951	0.4625
CoupledCF	0.8346	0.5648	0.8125	0.8093	0.5232	0.8007	0.6911	0.4548	0.6692	0.5190	0.2798	0.4927
Deeprank	0.7794	0.5173	0.7487	0.7753	0.5104	0.7460	0.6302	0.4059	0.6095	0.4672	0.2836	0.4431
AGMF	0.8515	0.5963	0.8346	0.9483	0.7652	0.9186	0.7078	0.4732	0.6789	0.3643	0.2153	0.3399
AMLP	0.8261	0.5485	0.8070	0.7212	0.5214	0.7006	0.6983	0.4376	0.6677	0.5162	0.3102	0.4927
ANeuMF	**0.8600**	**0.6072**	**0.8378**	**0.9592**	**0.7879**	**0.9328**	**0.7204**	**0.4913**	**0.7006**	**0.5364**	**0.3410**	**0.5112**

Attribute-based neural collaborative filtering(Expert Systems with Applications, 2020)

Conclusion

- NCF is considered to create an appropriate model that can be used by combining auxiliary information as well as evaluation scores of users and items without missing it.

- But how do I create a new model?

Multi-criteria collaborative filtering recommender by fusing deep neural network and matrix factorization(Journal of Big Data, 2020)

To Do List

- ✓ Read Top Conference Paper
- ✓ To check the data in paper

Thank you