

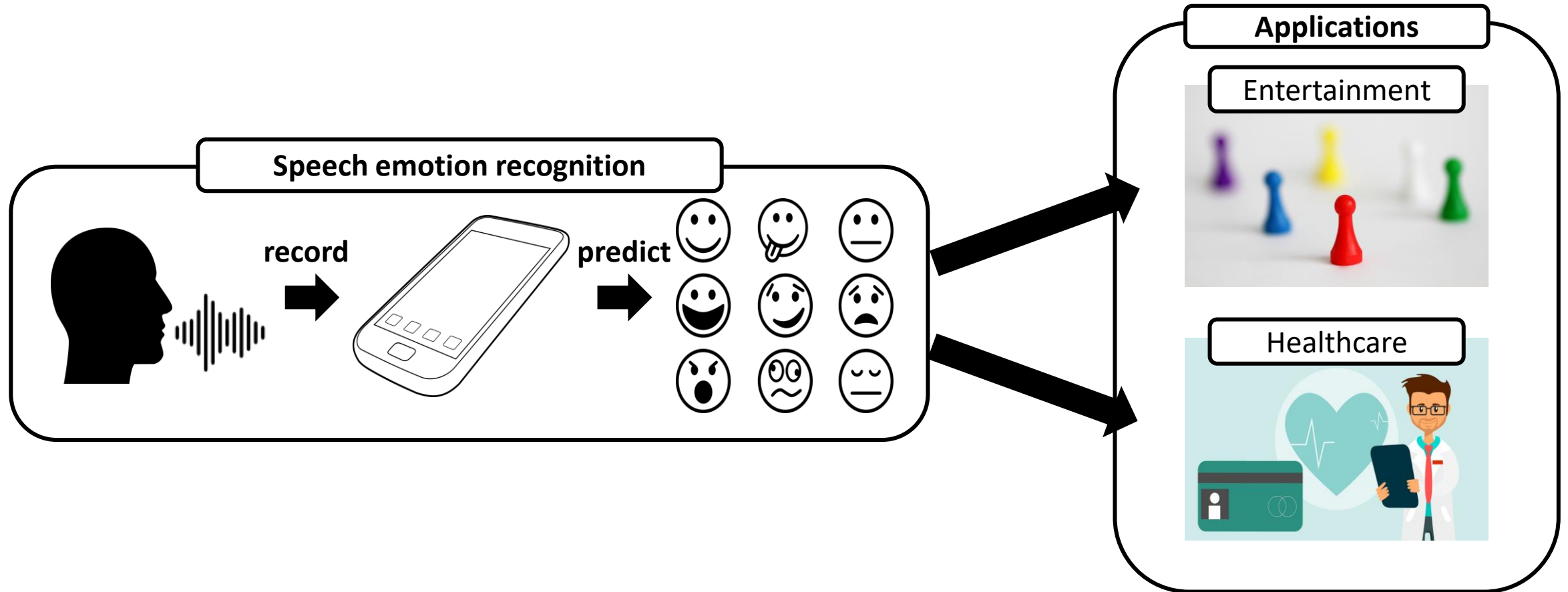


# Separation of Emotional and Reconstruction Embeddings on Ladder Network to Improve Speech Emotion Recognition Robustness in Noisy Conditions

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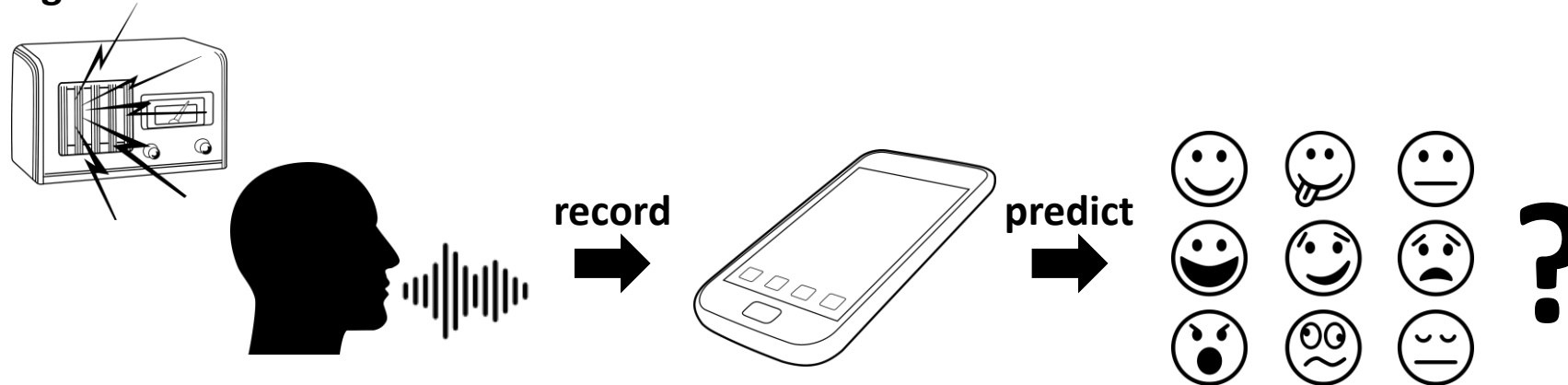


# Speech emotion recognition (SER) in real-world applications

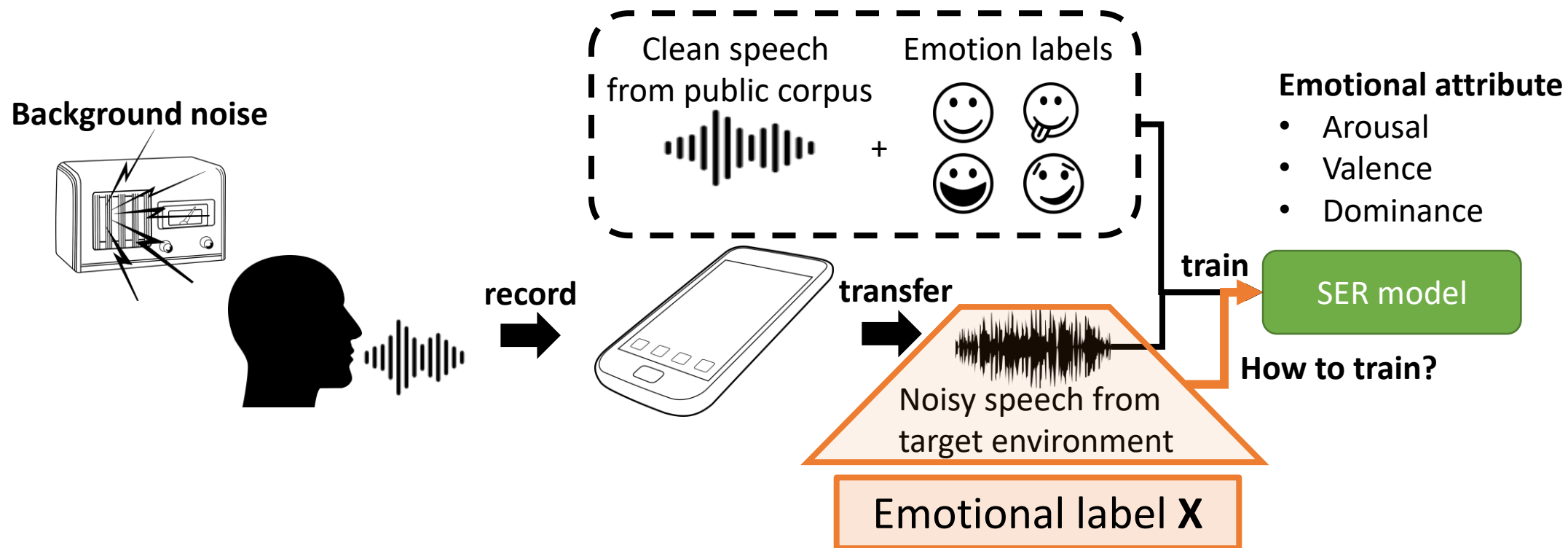


- **Needs to be robust against background noise**
  - Speech can be acquired from **unconstrained noisy environment**
  - Background noise can degrade the performance of SER system

Background noise



## Usage scenario



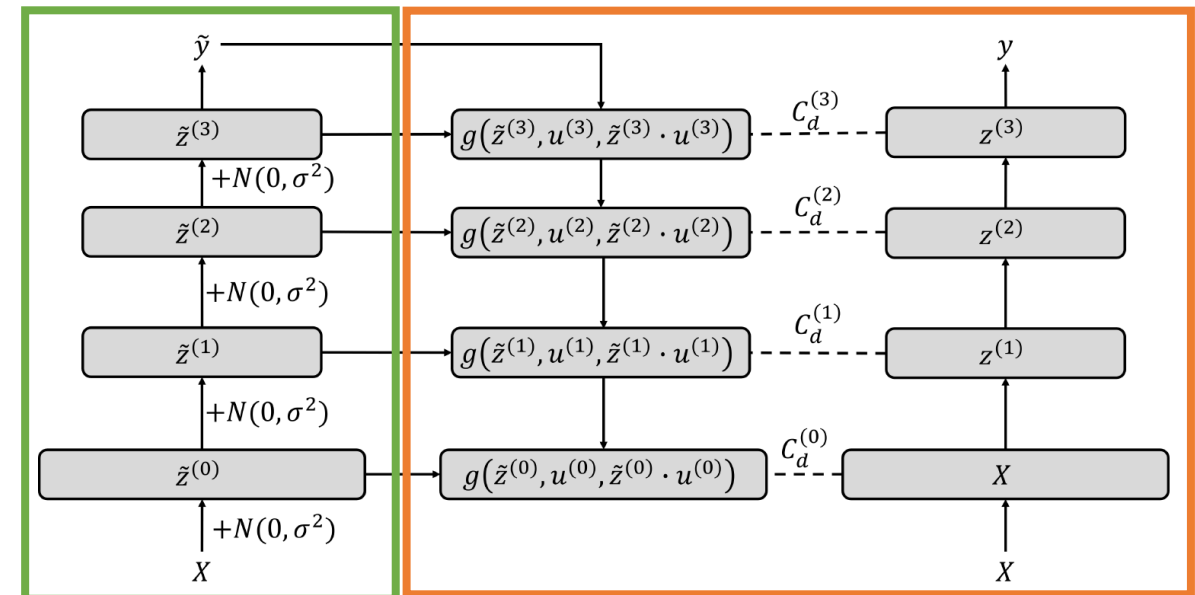
# Ladder network-based SER

## Strengths

- It does not require emotional labels for target domain recordings
- It can minimize train/test mismatch

## Training

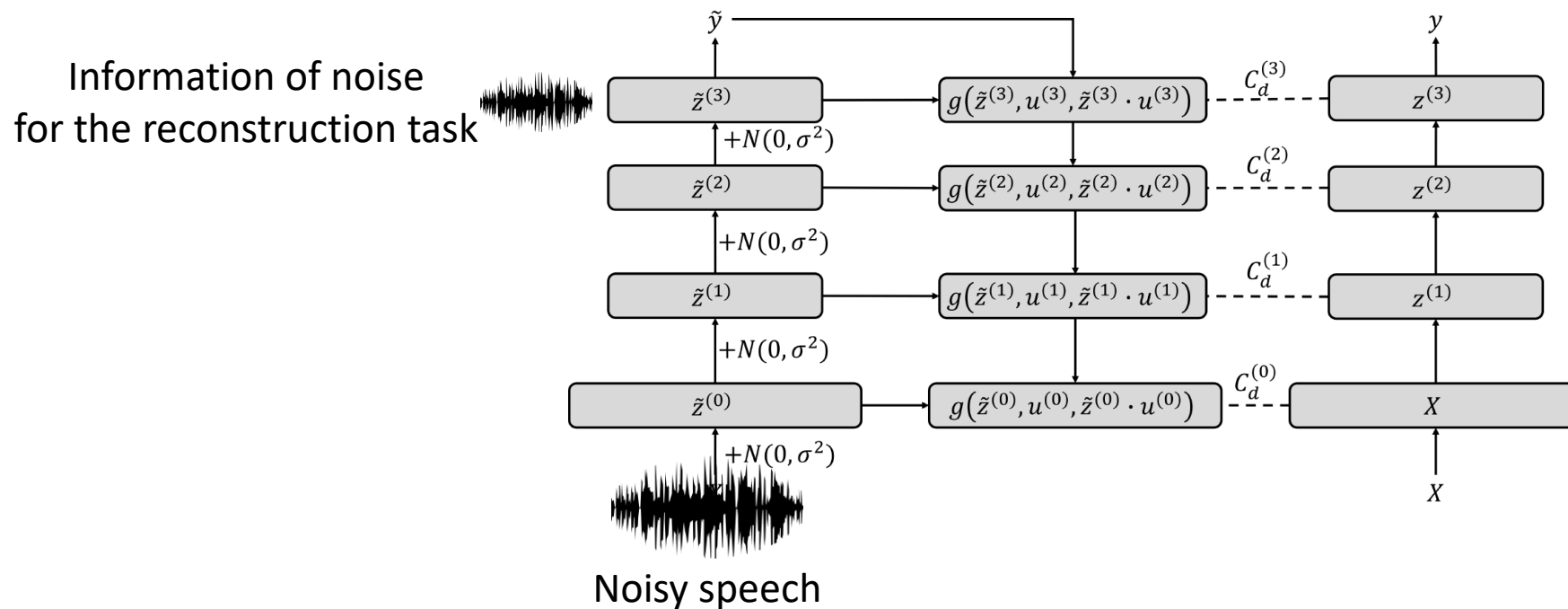
- Prediction task
  - Predict an emotional label by using labeled set
- Reconstruction task
  - Reconstruct clean representations for each hidden layer



# Ladder network for noise robust SER

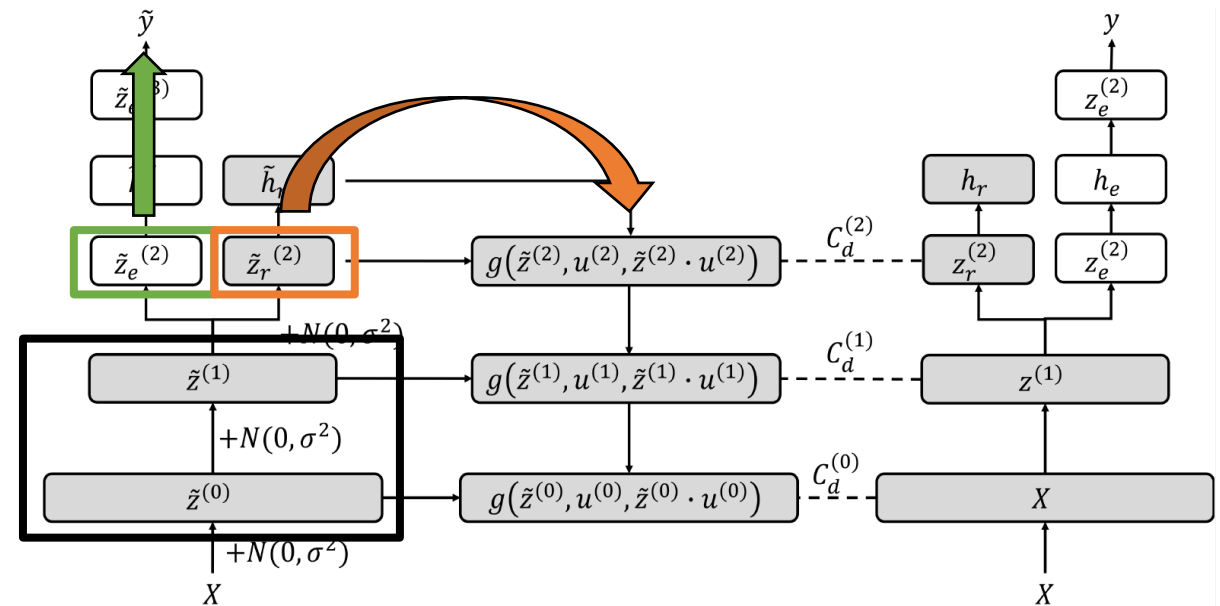
## Problem

- Audio samples contain complex background noises
  - It can disrupt the emotion prediction task



# Decoupled ladder network (DLN)

- **Solution**
  - Decouple last hidden layer into emotion and reconstruction embedding
- **Reconstruction embedding**
  - Reconstruction task
- **Emotion embedding**
  - Prediction task
- **Lower layers**
  - Prediction + reconstruction task



Decoupled ladder network architecture

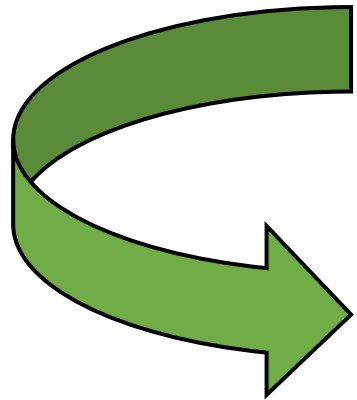
# Decoupled ladder network (DLN)

## Loss function

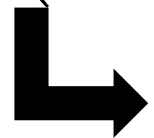
$$C_{DLN} = C_p \left( y, h_e^{(L)} \right) + \sum_{l=0}^{L-2} \lambda^l \times C_r^l \left( \hat{z}_{BN}^{(l)}, z^{(l)} \right) + \lambda^{L-1} \times C_r^{L-1} \left( \hat{z}_{BN}^{(L-1)}, z_r \right)$$

Prediction loss  
(for emotional attributes)

Reconstruction loss



$$1 - CCC \left( y, h_e^{(L)} \right)$$

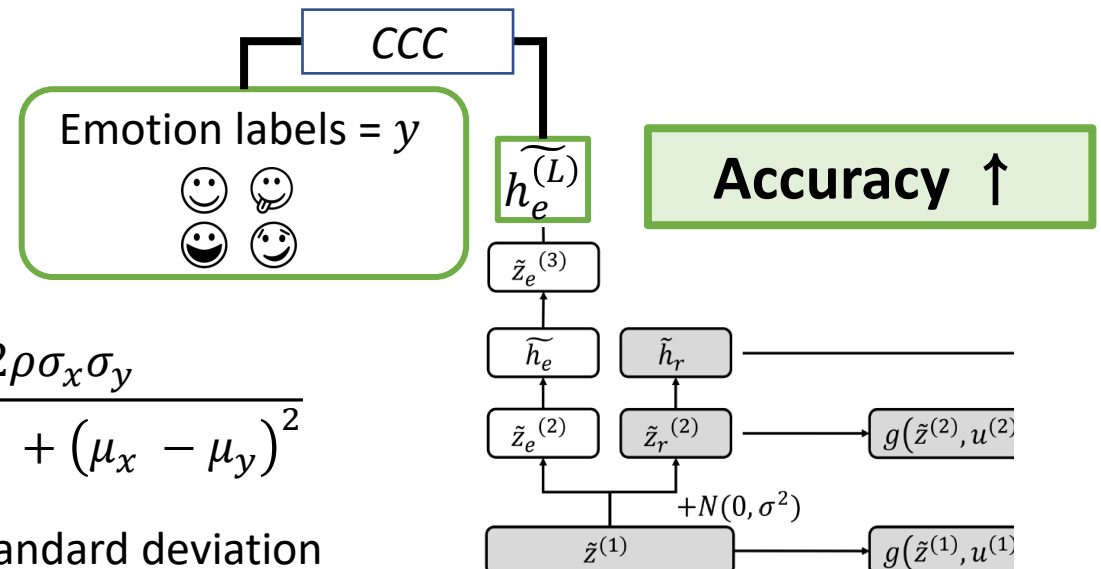


$$CCC(x, y) = \frac{2\rho\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2 + (\mu_x - \mu_y)^2}$$

$\sigma_x, \sigma_y$  : standard deviation

$\mu_x, \mu_y$  : mean

$\rho$ : correlation coefficient

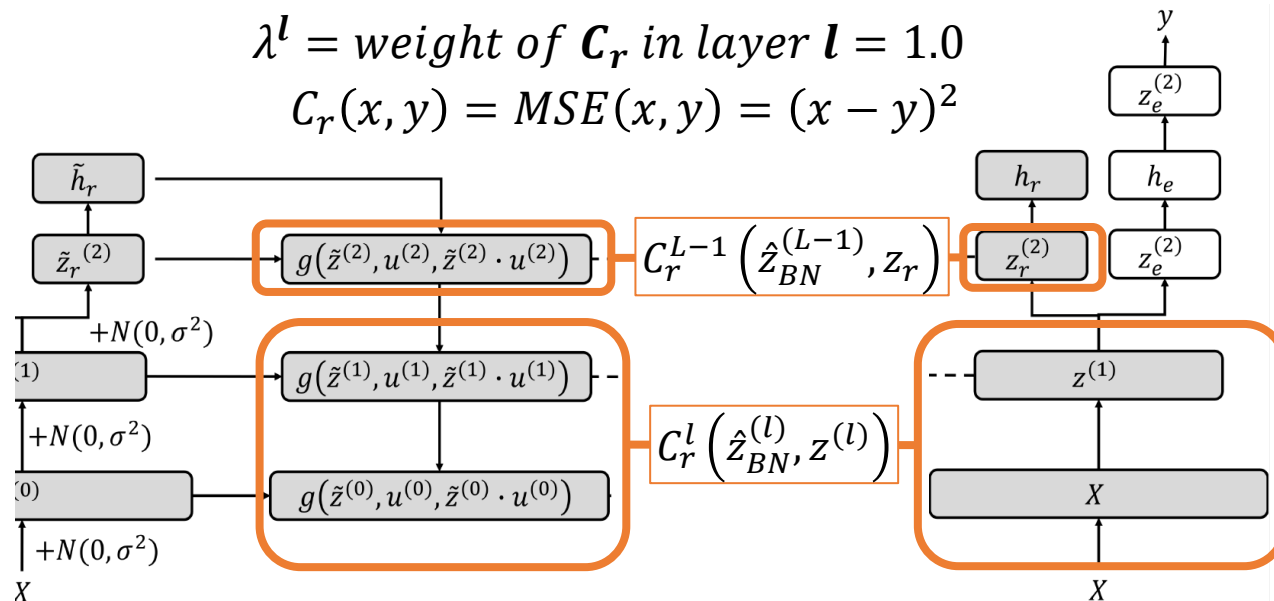




# Decoupled ladder network (DLN)

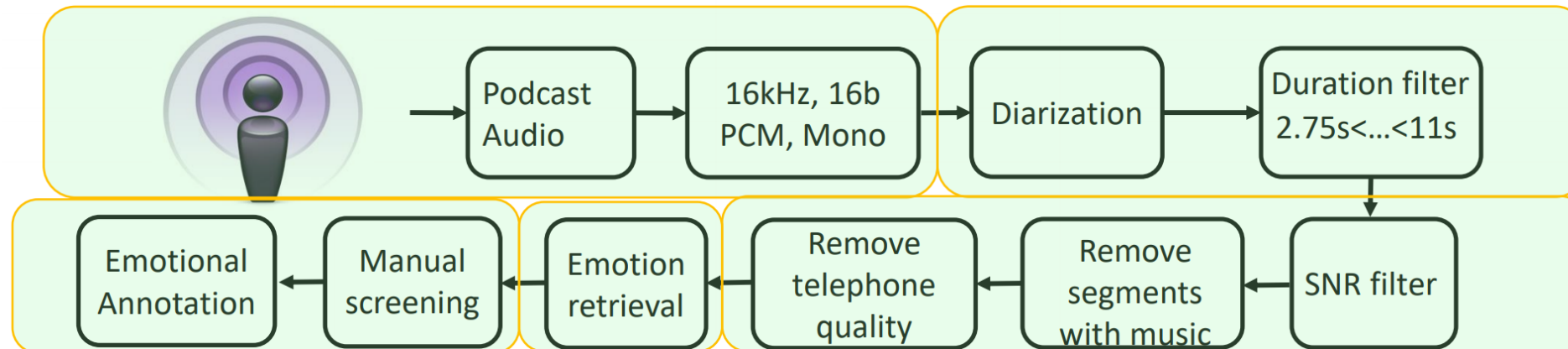
## Loss function

$$C_{DLN} = \underbrace{C_p \left( y, h_e^{(L)} \right)}_{\text{Prediction loss}} + \underbrace{\sum_{l=0}^{L-2} \lambda^l \times C_r^l \left( \hat{z}_{BN}^{(l)}, z^{(l)} \right) + \lambda^{L-1} \times C_r^{L-1} \left( \hat{z}_{BN}^{(L-1)}, z_r \right)}_{\text{Reconstruction loss}}$$



Difference ↓

- **Spontaneous emotional speech dataset**
  - Podcast recordings are collected (**> 113 hours**)
- **Clean speech dataset**
  - SNR is above 20dB



# Noisy version of the MSP-Podcast corpus

- **Noisy speech used in previous studies**

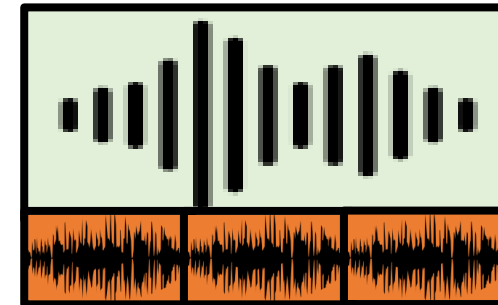
- Noisy speech had been artificially synthesized in previous works

- **Limitation**

- Not enough to simulate actual recording conditions



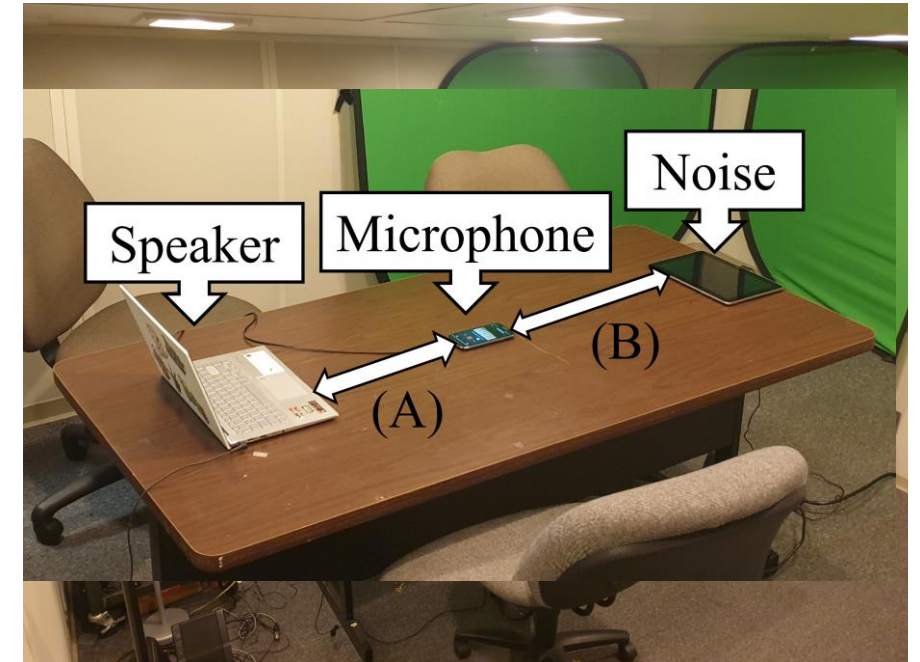
Fixed noise



Repeated noises

# Noisy version of the MSP-Podcast corpus

- **Solution**
  - Simultaneously playing the MSP-Podcast corpus and noise sound
  - Recording it with smartphone
- **Radio shows without copyright (noise)**
  - Simulating non-stational background noise
    - Human voice, musical sound, and sound effect



# Noisy version of the MSP-Podcast corpus

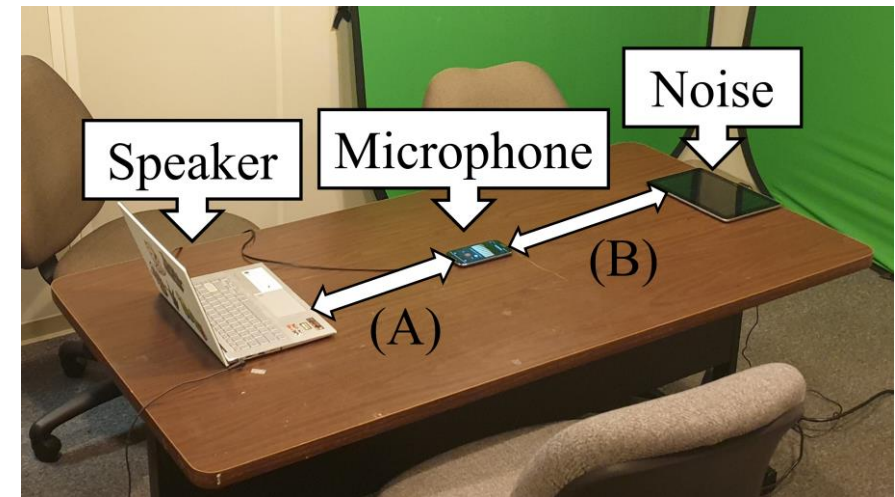
- **Settings for each recording conditions**

- 10dB, 5dB, 0dB conditions are collected

Recording condition	(A) (inch)	(B) (inch)	Estimated SNR (dB)
10dB	5	35	11.06
5dB	10	30	4.34
0dB	15	25	0.15

- **Emotional labels**

- Noise sound is not related to the emotion
- Emotional labels can be transferred from the MSP-Podcast corpus



# Experiment setting

## ■ Data preparation

- MSP-Podcast v1.8 (clean speech set)
- Noisy version of the MSP-Podcast corpus (noisy speech set)

Condition	Training	Development	Test	Unlabeled
Clean	44,879	7,800	15,326	43,361
Noisy (10dB, 5dB, 0dB)	-	-	15,326	43,361

- Recording condition between the test set and the unlabeled training set is matched

## ■ Acoustic features

- 6,373 dimensions of 2013 ComParE feature set is used

## ■ Baseline models

- Dense network
  - Model cannot use unlabeled set during training
- Ladder network
  - Its last hidden layer is not separated into emotion and reconstruction embedding
- All hyperparameters for the training and the number of layers, nodes are same as decoupled ladder network

- Concordance correlation coefficient (CCC)

- Average CCC over 20 trials

Task	Arousal				Valence				Dominance			
SNR	Clean	10dB	5dB	0dB	clean	10dB	5dB	0dB	clean	10dB	5dB	0dB
Dense network	<b>0.631</b>	0.248	0.229	0.192	<b>0.296</b>	0.151	0.120	0.104	<b>0.562</b>	0.253	0.252	0.215
Ladder network	0.627	0.438	0.424	0.364	0.280	0.146	0.129	0.111	0.545	0.381	0.385	0.339
Decoupled ladder network	0.625	<b>0.488</b>	<b>0.460</b>	<b>0.402</b>	0.283	<b>0.160</b>	0.126	0.114	0.556	<b>0.450</b>	<b>0.436</b>	<b>0.397</b>

Performance ↑
 Performance ↓

- Noisier speech shows lower performance than cleaner speech

- Background noise evokes detrimental effects on emotion prediction

- Ladder network shows better performance in noisy conditions than dense network

- Semi-supervised learning can improve the robustness against the noise



Task	Arousal				Valence				Dominance			
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**Performance ↑**

**No clear improvements**

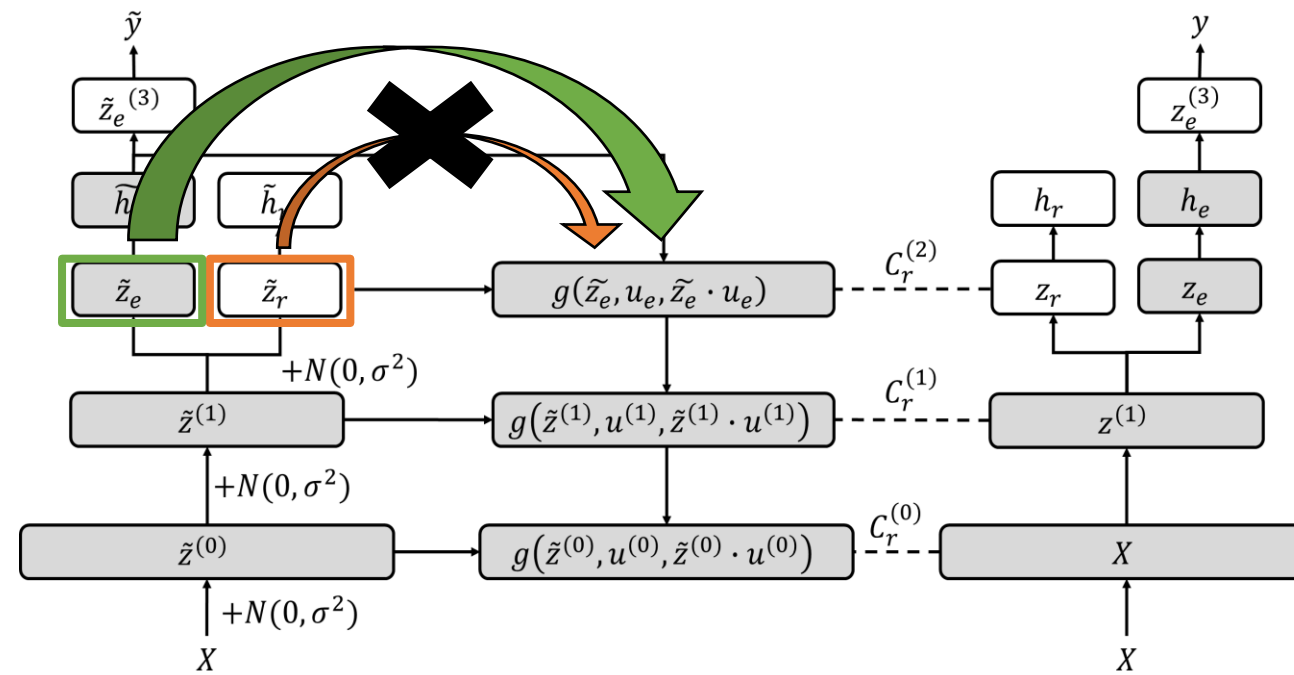
- **Decoupled ladder network improves the ladder network**

- Arousal: 11.4% (10dB), 8.4% (5dB), 10.2% (0dB) ↑
- Dominance: 17.1% (10dB), 13.2% (5dB), 7.0% (0dB) ↑

# Analysis on separating the embedding

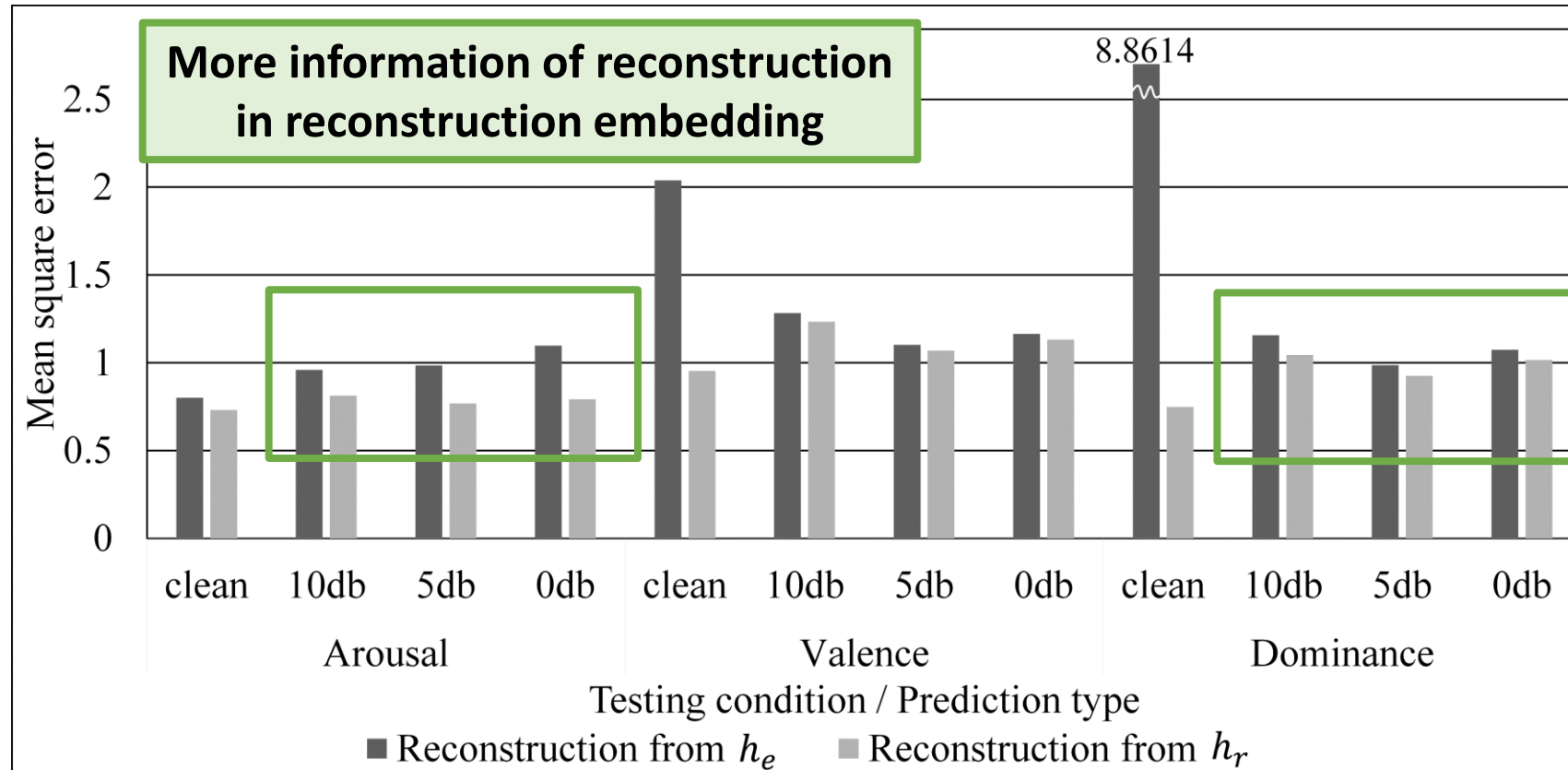
- **Reconstruction by using emotion embedding**

- Emotion embedding is fed into the highest layer of decoder
- Loss of using emotion embedding > Loss of using reconstruction embedding



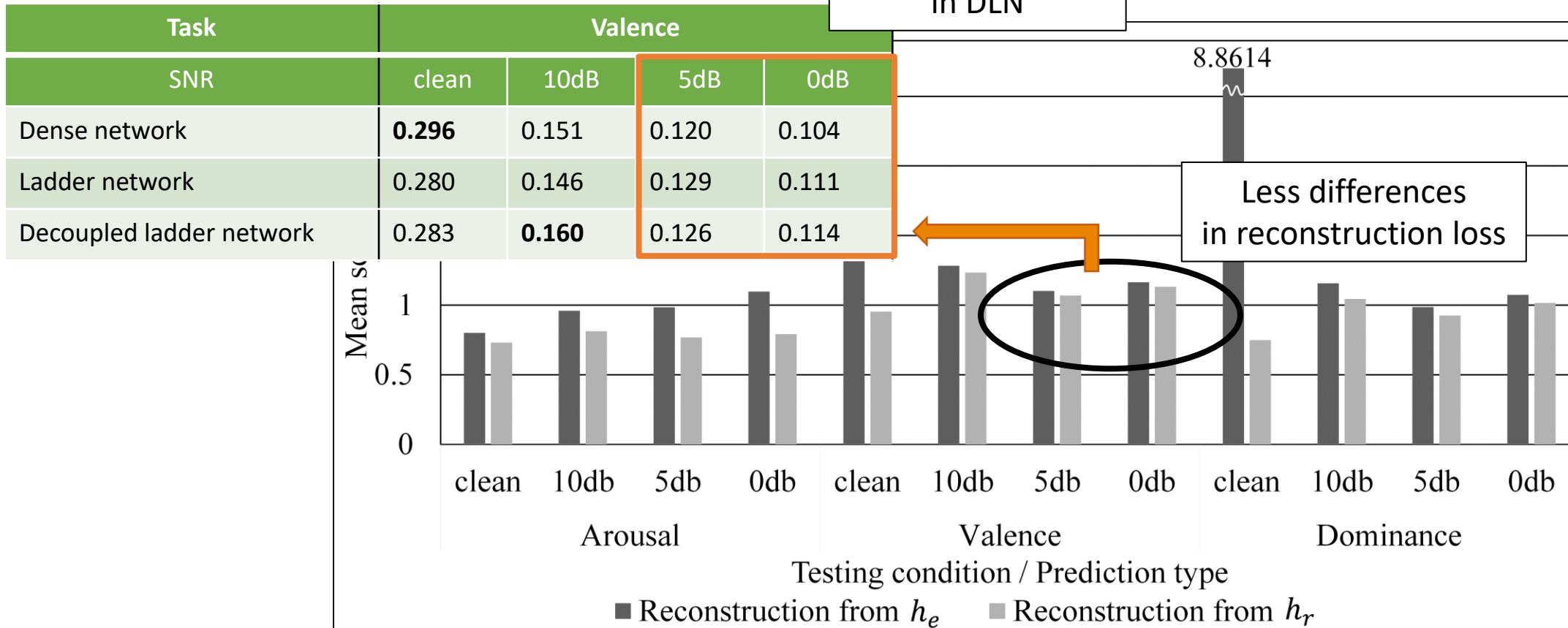
# Analysis on separating the embedding

- Reconstruction loss



# Analysis on separating the embedding

## Reconstruction loss

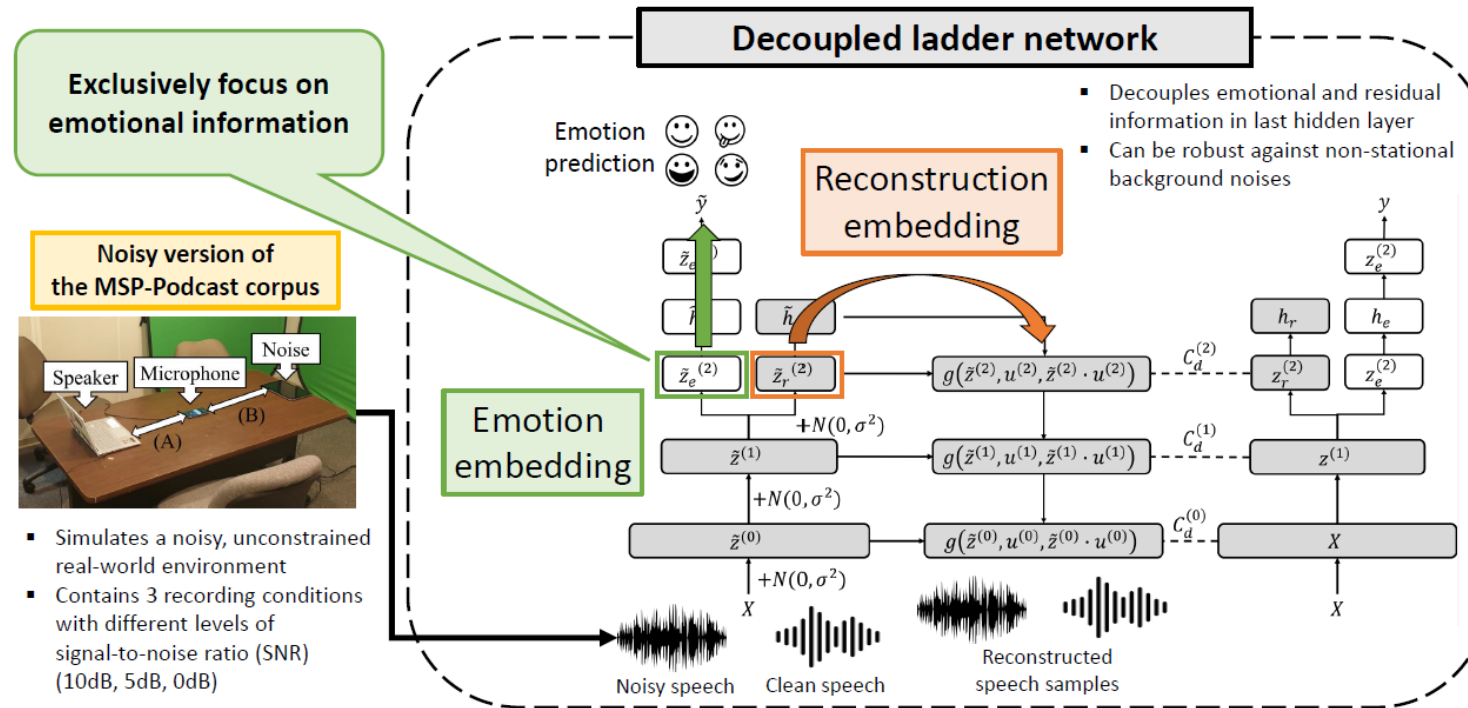


## Decouple ladder network

- Decouples the emotional and residual information to improve performance in noisy conditions

## Noisy version of the MSP-Podcast corpus

- Simulates noisy, unconstrained recording environment.



# Release of the MSP-Podcast corpus

## Academic license

- Federal Demonstration Partnership(FDP) Data Transfer and Use Agreement
- Free access to corpus

## Commercial license

- Commercial license through UT Dallas

## Plan to release the noisy version of the MSP-Podcast corpus

<https://msp.utdallas.edu>



**MSP-Podcast**

**MSP-Podcast corpus:**  
A large naturalistic speech emotional dataset

We are building the largest naturalistic speech emotional dataset in the community. The MSP-Podcast corpus contains speech segments from podcast recordings which are perceptually annotated using crowdsourcing. The collection of this corpus is an ongoing process. Version 1.7 of the corpus has 62,140 speaking turns (100hrs)

- Test set 1: We use segments from 60 speakers (30 female, 30 male) - 12,902 segments
- Test set 2: We randomly select 3,521 segments from 100 podcasts. Segments from these podcasts are not included in any other partition.
- Development set: We use segments from 44 speakers (22 female, 22 male) - 7,538 segments
- Train set: We use the remaining speech samples - 38,179 segments

**MSP-PODCAST Corpus**  
Scalable framework to collect a large emotional database

```

    graph TD
      A[Podcast Audio] --> B[16kHz, 30s  
PCM, Mono]
      B --> C[Duration Filter  
2.75m-~11m]
      C --> D[Remove segments  
with noise]
      D --> E[Spontaneous speech emotional data]
      F[Emotional Annotation] --> G[Manual screening]
      G --> H[Emotion retrieval]
      H --> I[Remove telephone  
quality]
      I --> J[Remove segments  
with noise]
      J --> K[Skill Filter]
      K --> E
      L[Use existing podcast recordings] --> E
      M[Emotion retrieval to balance the emotional content] --> E
      N[Annotate using crowdsourcing framework] --> E
  
```

Prospective students

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- **Questions or Contact: Seong-Gyun Leem**
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