# Supervised Speech Representation Learning for Parkinson's Disease Classification

Parvaneh Janbakhshi and Ina Kodrasi

Idiap Research Institute

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# Outline

1. Automatic PD Speech Classification
2. State-of-the-art
3. Proposed Method
4. Experimental Results
5. Summary

# Automatic PD speech classification

- Parkinson's disease (PD) $\rightarrow$ disturbances of muscular control on speech production system
  - Imprecise articulation, abnormal speech rhythm, reduced stress, breathiness

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PD speech classification using:

- Subjective screening based on judgement of medical practitioners
  - Labor-intensive
  - Inconsistency
  - Difficulties with early diagnosis

- Automatic and objective method
  - Efficient and economical
  - Repeatable
  - Early diagnosis

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- Deep learning approaches

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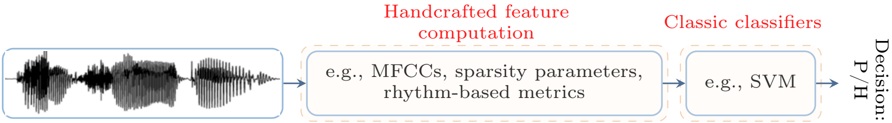


# State-of-the-art automatic PD speech classification systems

» Traditional machine learning approaches (Hegde et al., 2019; Kodrasi and Bourlard, 2020; Hernandez et al., 2020)


⚠ May fail to adequately capture pathological speech characteristics

⚠ May fail to characterize abstract but important acoustic cues

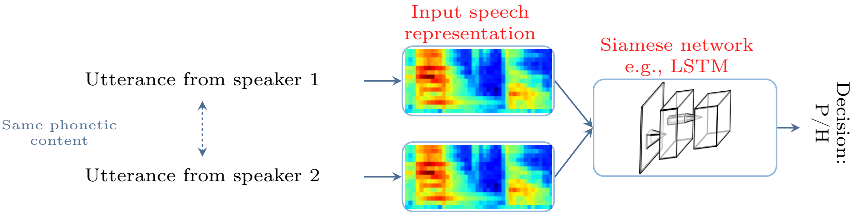
# State-of-the-art automatic PD speech classification systems

- Deep learning approaches → data-driven approaches using no prior knowledge
  - Exploit high-level abstract features from low-level speech representations or raw waveforms using neural networks
  - Challenge: guiding networks to learn robust and relevant features with limited available pathological training data

# State-of-the-art automatic PD speech classification systems

- Deep learning approaches
  - Pairwise training using LSTM Siamese networks (Bhati et al., 2019)

    ⚠ Different networks for different utterances

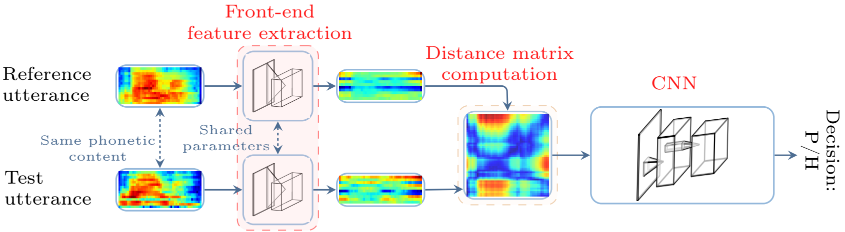


# State-of-the-art automatic PD speech classification systems

» Deep learning approaches

- Pairwise training using distance-based CNNs (Janbakhshi et al., 2021)

⚠ A single network for different but phonetically matched utterances

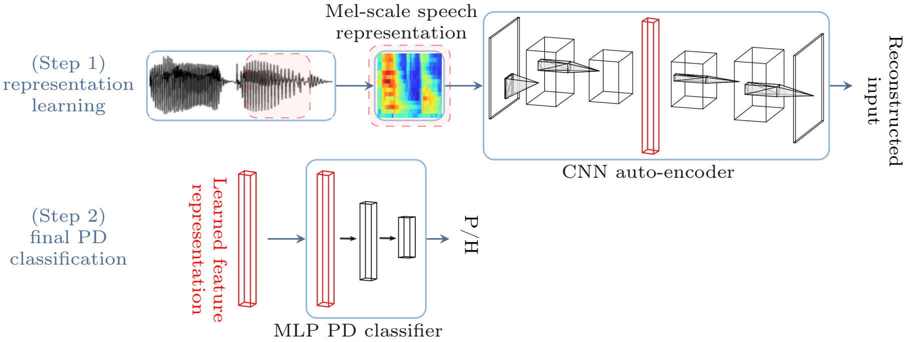


# State-of-the-art automatic PD speech classification systems

» Deep learning approaches

- Unsupervised representation learning (Vasquez-Correa et al., 2020; Karan et al., 2020)

⚠ Learned representations may not be robust to pathology-unrelated cues, e.g., speaker identity and may not be discriminative for pathology detection



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# Supervised speech representation learning for PD classification

1. Speaker identity-invariant representation with adversarial training
   - Jointly minimizing the auto-encoder reconstruction loss and minimizing the performance of a (neurotypical) speaker identification (ID) task
   - Improved performance in tasks, e. g., speech emotion classification and phoneme/senone discrimination (Li et al., 2020; Higuchi et al., 2019; Meng et al., 2018)

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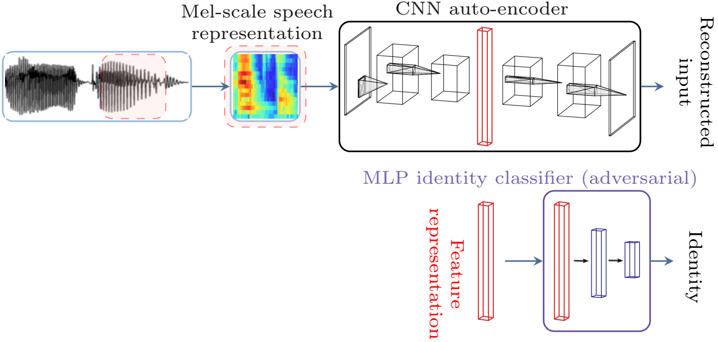
2. PD discriminative representation
   - Jointly minimizing the auto-encoder reconstruction loss and maximizing the PD classification performance
   - Such supervision does not harm the performance since the reconstruction loss acts as a regularization method (Le et al., 2018)

# Supervised speech representation learning for PD classification

» Speaker identity-invariant representation (adversarial training)

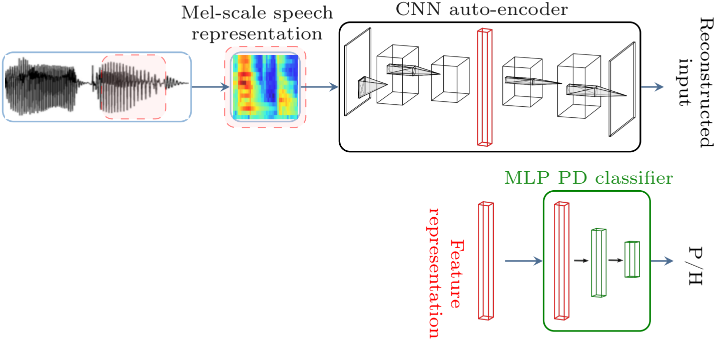



(Step 1)
representation
learning

# Supervised speech representation learning for PD classification

» PD discriminative representation

(Step 1) representation learning



# Supervised speech representation learning for PD classification

» Fusion; speaker identity-invariant **and** PD discriminative representation

(Step 1)
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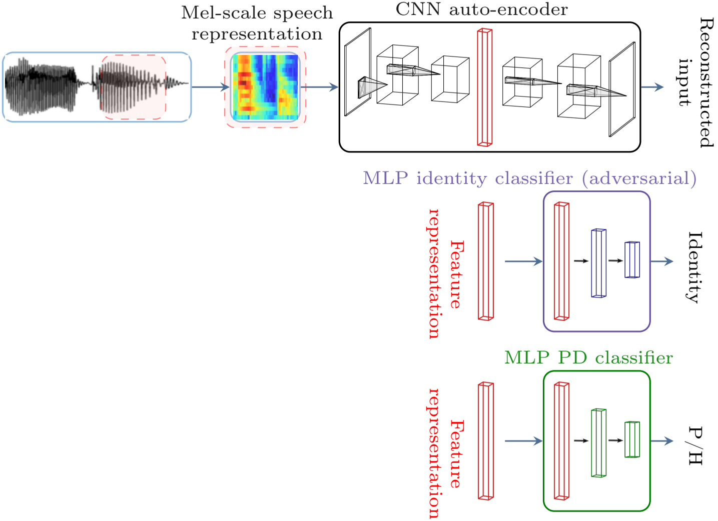


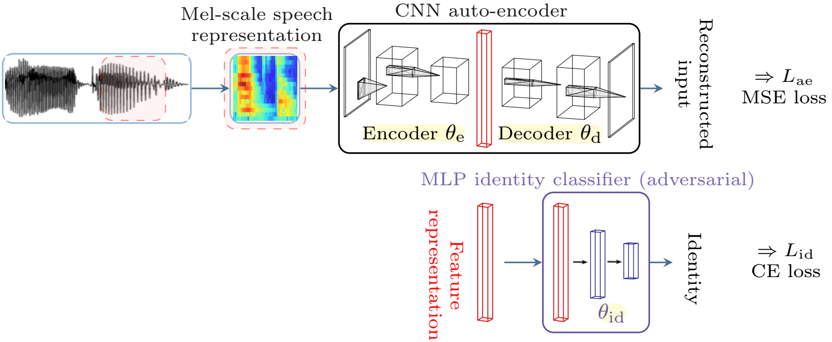
# Supervised speech representation learning for PD classification

» Speaker identity-invariant representation training → min-max objective

$$(\hat{\theta}_{\mathrm{e}}, \hat{\theta}_{\mathrm{d}}, \hat{\theta}_{\mathrm{id}}) = \arg\min_{\theta_{\mathrm{e}}, \theta_{\mathrm{d}}} \arg\max_{\theta_{\mathrm{id}}} E(\theta_{\mathrm{e}}, \theta_{\mathrm{d}}, \theta_{\mathrm{id}}), \tag{1}$$

$$E(\theta_{\mathrm{e}}, \theta_{\mathrm{d}}, \theta_{\mathrm{id}}) = (1-\lambda) L_{\mathrm{ae}}(\theta_{\mathrm{e}}, \theta_{\mathrm{d}}) - \lambda L_{\mathrm{id}}(\theta_{\mathrm{e}}, \theta_{\mathrm{id}}) \tag{2}$$

- Parameters estimating by alternating training procedure
- Data from neurotypical speakers is used to optimize $L_{\mathrm{id}}$



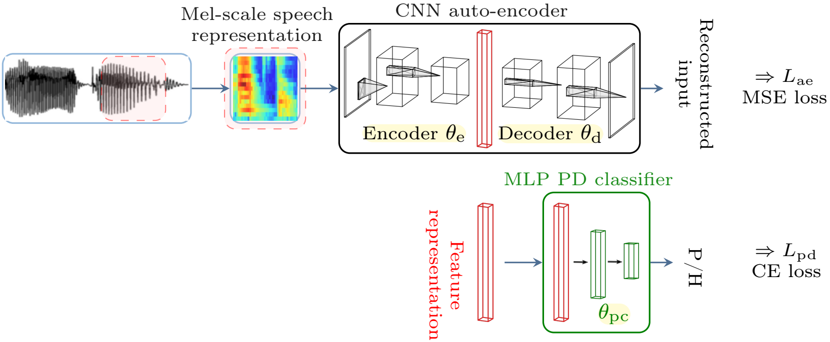
# Supervised speech representation learning for PD classification

» PD discriminative representation training

$$(\hat{\theta}_{\mathrm{e}}, \hat{\theta}_{\mathrm{d}}, \hat{\theta}_{\mathrm{pc}}) = \arg \min_{\theta_{\mathrm{e}}, \theta_{\mathrm{d}}, \theta_{\mathrm{pc}}} E(\theta_{\mathrm{e}}, \theta_{\mathrm{d}}, \theta_{\mathrm{pc}}), \tag{3}$$

$$E(\theta_{\mathrm{e}}, \theta_{\mathrm{d}}, \theta_{\mathrm{pc}}) = (1-\alpha) L_{\mathrm{ae}}(\theta_{\mathrm{e}}, \theta_{\mathrm{d}}) + \alpha L_{\mathrm{pc}}(\theta_{\mathrm{e}}, \theta_{\mathrm{pc}}) \tag{4}$$

- Optimal parameters → simultaneously minimizing $L_{\mathrm{ae}}$ and $L_{\mathrm{pd}}$



# Supervised speech representation learning for PD classification

» Fusion

- Jointly learn a speaker identity-invariant and PD discriminative representation → min-max objective

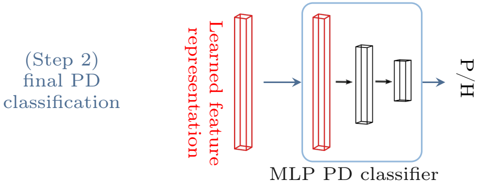
$$(\hat{\theta}_{\mathrm{e}}, \hat{\theta}_{\mathrm{d}}, \hat{\theta}_{\mathrm{pc}}, \hat{\theta}_{\mathrm{id}}) = \arg \min_{\theta_{\mathrm{e}}, \theta_{\mathrm{d}}, \theta_{\mathrm{pc}}} \arg \max_{\theta_{\mathrm{id}}} E(\theta_{\mathrm{e}}, \theta_{\mathrm{d}}, \theta_{\mathrm{pc}}, \theta_{\mathrm{id}}), \tag{5}$$

$$E(\theta_{\mathrm{e}}, \theta_{\mathrm{d}}, \theta_{\mathrm{pc}}, \theta_{\mathrm{id}}) = (1 - \alpha - \lambda) L_{\mathrm{ae}}(\theta_{\mathrm{e}}, \theta_{\mathrm{d}}) + \alpha L_{\mathrm{pc}}(\theta_{\mathrm{e}}, \theta_{\mathrm{pc}}) - \lambda L_{\mathrm{id}}(\theta_{\mathrm{e}}, \theta_{\mathrm{id}}) \tag{6}$$

# Supervised speech representation learning for PD classification

» Final PD classification
  - Training the final PD speech classifier operating on the learned feature (bottleneck) representation

» Evaluating an unseen test speaker
  - Applying soft voting on the classifier prediction scores for all input Mel spectrograms belonging to that speaker



# Outline

# Experimental results

- Dataset: Spanish PC-GITA database (Orozco et al., 2014)
  - 50 PD patients vs. 50 healthy speakers each uttering 24 words, 10 sentences, and 1 text
  - PD classification task train/evaluation data → Speaker-independent 10-fold cross-validation framework
  - Speaker ID auxiliary task train/evaluation data → utterance splits of neurotypical speakers in the training set (i.e., 45 speakers)
- Evaluation metrics
  - PD classification accuracy: percentage of correctly classified neurotypical and PD speakers
  - Speaker ID accuracy: percentage of correctly identified speakers
  - AUC: area under ROC curve

# Experimental results

- Tuning hyper-parameters $\lambda$ and $\alpha$ for each speaker identity-invariant and PD discriminative representation training tasks
  - Grid-search (selecting values yielding the highest PD classification accuracy on the development set)
- Hyper-parameters for fusion approach $\rightarrow$ not optimized but set to the values obtained above

# Experimental results

- PD classification performance
  - Baseline (unsupervised) representation learning without auxiliary tasks
  - Supervised representation learnings through auxiliary tasks

| Auxiliary task in representation learning | Accuracy[%] | AUC |
|---|---|---|
| No auxiliary task (baseline) | 66.20 | 0.77 |
| Adversarial identity-invariant training | 72.00 | **0.84** |
| PD discriminative training | 71.00 | 0.78 |
| Fusion (identity-invariant+PD discriminative training) | **75.40** | 0.80 |

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- Any of the proposed auxiliary tasks improves the performance of PD classification compared to the baseline
- Fusing both auxiliary tasks yields a better accuracy

# Experimental results

Investigating the suppression of irrelevant speaker identity information in the learned representations

» Speaker ID performance

| Auxiliary task in representation learning | Accuracy[%] | AUC |
|---|---|---|
| No auxiliary task (baseline) | 34.71 | 0.90 |
| Adversarial identity-invariant training | 2.31 | 0.54 |
| PD discriminative training | 18.15 | 0.76 |
| Fusion (identity-invariant+PD discriminative training) | 2.59 | 0.58 |

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- Highest speaker ID performance using unsupervised representation → speaker identity cues reduce PD classification performance
- Lowest speaker ID performance using the speaker identity-invariant representation
- Lower speaker ID performance using PD discriminative representation → speaker identity cues are less relevant to the PD classification task

# Outline

# Summary

- Using supervised representation learning frameworks with auxiliary tasks for PD classification
- Reducing irrelevant speaker identity cues in the representation
  - Training an auto-encoder jointly with an adversarial auxiliary speaker ID task
- Obtaining a discriminative representation for PD classification
  - Training an auto-encoder jointly with an auxiliary PD classifier
- Supervised representation learning is advantageous for PD classification, outperforming using representations learned in an unsupervised manner

*Thank You*

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