# Automatic Selection of Discriminative Features for Dementia Detection in Cantonese-Speaking People


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## Introduction

Dementia is a severe cognitive impairment that may seriously affect the health and daily lives of the old adults [1]. The most common form of dementia is Alzheimer's Disease (AD). Fortunately, with effective detection of early dementia, disease-modifying medications and interventions are possible.

Dementia can be diagnosed through several means, including neuropsychological assessments, brain scans, blood tests, etc. These methods are generally **intrusive** and **costly**.

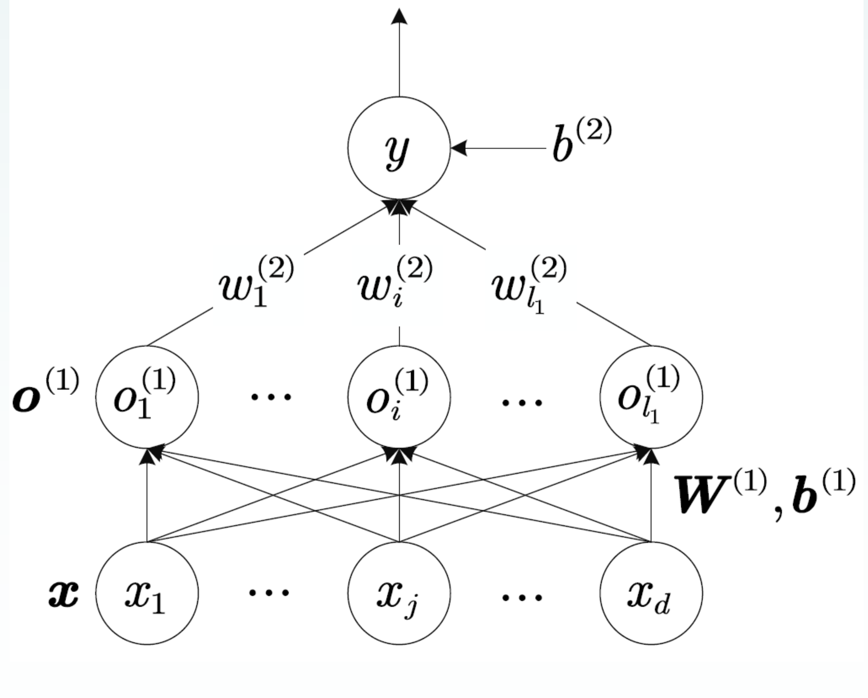
Dementia also manifests itself as spoken language deficits:

◆Dementia-induced language impairment could be found in patients years before the disease was diagnosed.

◆Individuals with progressive cognitive decline exhibit subtle linguistic impairment even in the pre-stages of the disease.

Dementia can be detected using spoken language processing (SLP) techniques.

## Variable Selection in Neural Networks




A 2-layer neural network

Given a $d$-dimensional input vector $\boldsymbol{x}$, the output of the hidden layer is:

$$\boldsymbol{o}^{(1)} = g\left(\left(\boldsymbol{W}^{(1)}\right)^{\mathsf{T}} \boldsymbol{x}\right) \in \mathbb{R}^{l_1}.$$

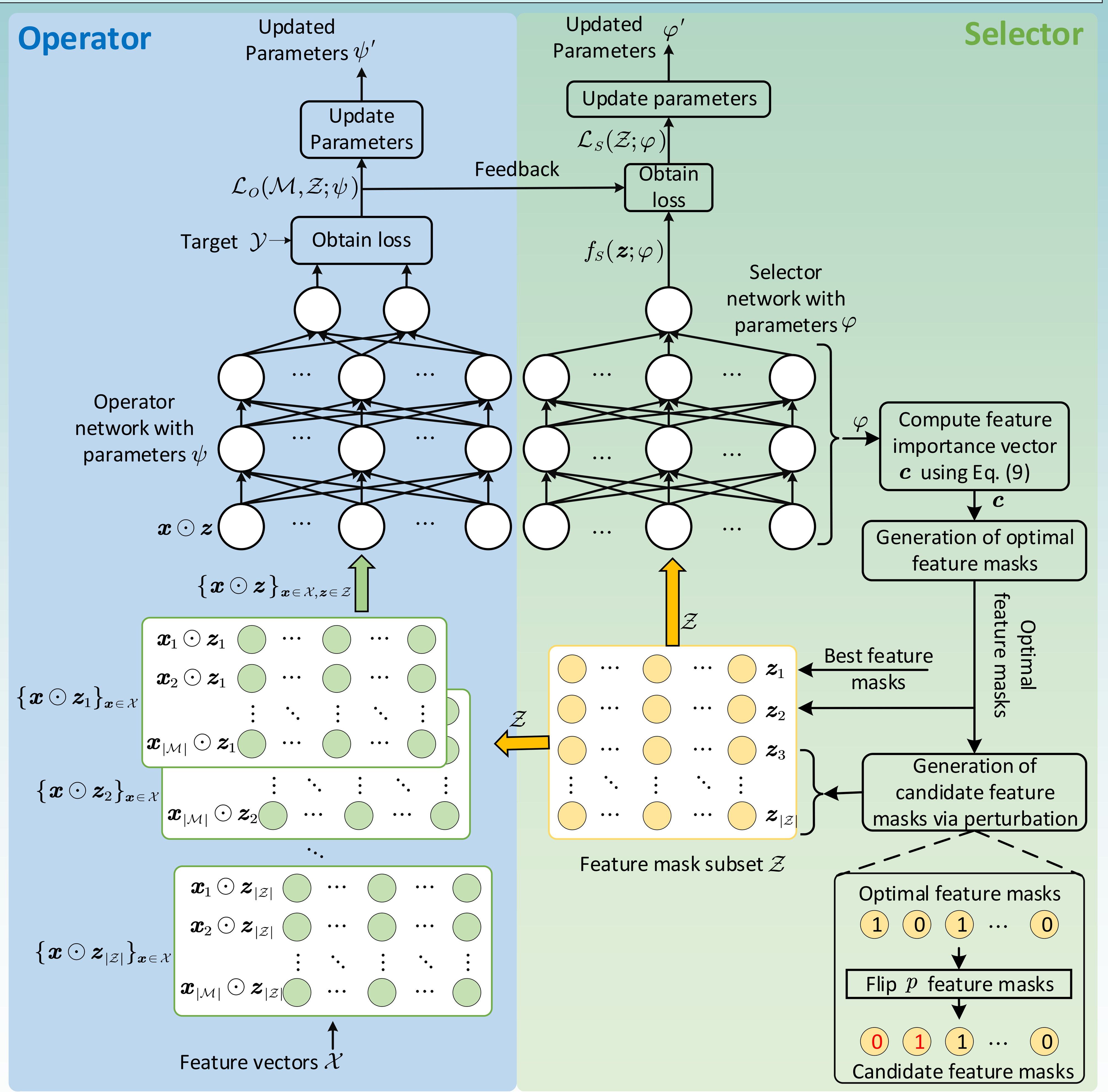
The feature important vector for the two-layer neural network:

$$g\left(\boldsymbol{W}^{(1)}\right)\boldsymbol{w}^{(2)}$$

The feature important vector for a $L$-layer neural network:

$$\boldsymbol{c} = g\left(g\left(g\left(\boldsymbol{W}^{(1)}\right)\boldsymbol{W}^{(2)}\right)\cdots\boldsymbol{W}^{(L-1)}\right)\boldsymbol{w}^{(L)}$$

## Feature Selection




Operator's objective: $\mathcal{L}_O(\mathcal{M}, \mathcal{Z}; \psi) = \dfrac{1}{|\mathcal{Z}||\mathcal{M}|} \sum_{\boldsymbol{z} \in \mathcal{Z}} \sum_{(\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{M}} l(\boldsymbol{x} \odot \boldsymbol{z}, \boldsymbol{y}; \psi)$

Selector's objective: $\mathcal{L}_S(\mathcal{Z}; \varphi) = \dfrac{1}{|\mathcal{Z}|} \sum_{\boldsymbol{z} \in \mathcal{Z}} \left\{ \left| f_S(\boldsymbol{z}; \varphi) - \dfrac{1}{|\mathcal{M}|} \sum_{(\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{M}} l(\boldsymbol{x} \odot \boldsymbol{z}, \boldsymbol{y}; \psi) \right| \right\}$

The operator is trained on the features obtained from the selector to reduce classification loss.

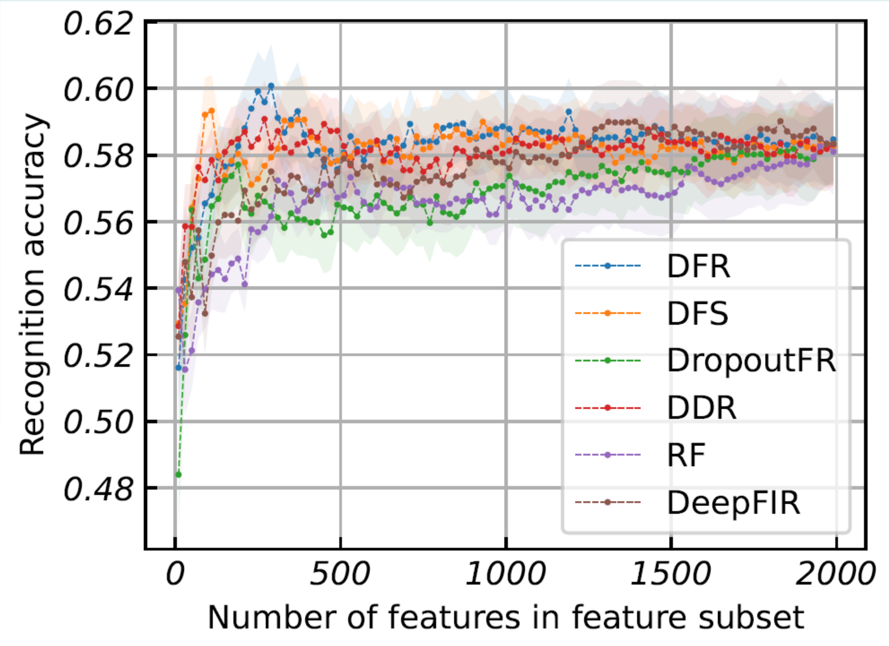
The selector learns to predict the operator's learning performance using the selected features

## Experiments and Results

| JCCOCC-MoCA | |
|---|---|
| Language | Cantonese |
| Task | fluency tests (animals, fruits, and vegetables), |
| Number of subjects | 43 (healthy subjects) vs. 43 (Possible NCD) |
| Number of samples | 129 samples for the healthy subjects, and 129 samples for the possible NCD |
| Classification | 2 classes |
| Manual transcripts | Yes |

Classification performance of different feature types on the JCCOCC-MoCA dataset.

| Feature set | 5 repetitions of leave-n-subject-out CV ACC | PRE | REC | F1 |
|---|---|---|---|---|
| Lexical (113) | 0.541 | 0.555 | 0.556 | 0.532 |
| ELECTRA (768) | 0.572 | 0.576 | 0.577 | 0.557 |
| Pause (30) | 0.550 | 0.557 | 0.560 | 0.539 |
| Acoustic (30) | 0.481 | 0.486 | 0.488 | 0.463 |
| COVAREP (518) | 0.389 | 0.409 | 0.419 | 0.376 |
| IS10 (1582) | 0.519 | 0.535 | 0.539 | 0.508 |
| Emobase (988) | 0.531 | 0.544 | 0.551 | 0.518 |
| eGeMAPS (88) | 0.533 | 0.545 | 0.548 | 0.522 |
| All features (4117) | **0.584** | **0.590** | **0.591** | **0.566** |




Classification performance under different number of selected features on the JCCOCC-MoCA dataset

## References


[1] https://www.who.int/news-room/fact-sheets/detail/dementia