DOMAIN AND SPEAKER ADAPTATION FOR CORTANA SPEECH RECOGNITION Yong Zhao, Jinyu Li, Shixiong Zhang, Liping Chen, and Yifan Gong Microsoft AI and Research

Introduction					
 Voice assistant represents one of the most popular and important scenarios for speech recognition 					
 We propose a deep adaptation framework that adapts a generic acoustic model towards Cortana assistant 					
-Anchor word speaker embedding					
 Adapting multiple layers in both weight matrices and biases 					
-Prior interpolation					
 The proposed system yields 32% WERR over the SI baseline 					
Prior Works and Motivation					
I-vector Based Adaptation on 1-st layer					
$m{z}_{s}^{1} = m{W}^{1}m{x} + m{V}m{e}_{s} + m{b}^{1}$					
• Pros					
-No need to retrain model parameters					
-No need to store speaker profile, if i-vector is estimated per utterance					
Cons					
–I-vector estimation over a short utterance is very noisy					
-Recognition starts until the utterance is finished					
 Low-Rank Plus Diagonal (LRPD) Adaptation A transformation matrix is very close to an identity matrix 					
• LRPD adaptation $W_{s,k \times k} \approx I_{s,k \times k} + P_{s,k \times c}Q_{s,c \times k}$ -# of SD parameters: $2ck + k$					
• Extended LRPD adaptation $W_{s,k\times k} \approx I_{s,k\times k} + P_{k\times c}T_{s,c\times c}Q_{c\times k}$ -# of SD parameters: $c^2 + c$					



 Prior interpolation between the source domain and the target domain

 $\hat{p}(q_t) = (1-\rho)\tilde{p}(q_t) + \rho p^{SI}(q_t)$

Analogous to Kullback-Leibler (KL) regularization

Experiments and Results

Experimental Data

• Train: 3400hr multi-style US English data • Dev: 220hr Cortana desktop data that begin with "Hey Cortana" within the 3400hr data Eval: Hey Cortana desktop test set

Experimental Setup

SI DNN

- -8 layers: 2,048*6:4,096:9,801
- -Input: 11 frames of 80-dim LFB + Δ + Δ^2
- Anchor embedding (100 dim)
- –I-vector: 39-dim MFCC, 512 mixture UBM
- D-vector: 5-layer DNN, 1024*4:100:8398
- Auxiliary networks
- -Two sigmoid layers each with 100 nodes followed by a linear layer
- -Reshape \boldsymbol{u}_{S}^{l} into \boldsymbol{U}_{S}^{l} of size 10×10

Baseline Performance

Table 1: WER (%) of the SI and SAT models on the Hey Cortana desktop test set.

Model	WER (%)
3400hr SI	16.36
220hr SI	20.20
220hr SAT, L1 ivec bias	17.49
220hr SAT, L1 dvec bias	16.64

Speaker Adaptation Using Anchor Embedding

 Adapting multiple layers (L1-*) outperforms adapting a single layer

Adapting the weight matrix only of multiple layers suffices to yield optimal performance



Fig. 2: WERs (%) for adapting biases and weight matrices of single layer and multiple layers from bottom to top using the anchor dvectors. The dashed level line is the 3400hr SI baseline.

Fig. 3: WERs (%) against prior interpolation weights ρ for three adaptation models. The dashed level line is the SI baseline.

Anchor-Based Adaptation with Prior Interpolation

Table 4: WERs (%) for the anchor-based speaker adaptation using i-vector and d-vector embeddings with prior interpolation $\rho = 0.5$.

Analysis of Recognition Results





Adaptation with Prior Interpolation

 Directly adapting the softmax layer (L8) with prior interpolation ($\rho = 0.5$) yields 20% WERR Adapting the softmax layer without changing the priors ($\rho = 1$) yields only 3% WERR Adapting the priors alone yields 4% WERR



• Anchor-based model (L1-7 dvec weight, $\rho = 0.5$) yields 32% WERR

 Adaptation using the anchor d-vector outperforms using the anchor i-vector

Model	ivec	dvec
L1-7 weight	11.66	11.06
L8 + L1-7 weight	11.42	11.02

Table 2: Top 10 word count changes from the SI model to the model
 with layer L8 updated ($\rho = 1$) on Hey Cortana desktop test set.

	Ref	SI	L8 ($\rho = 1$)	L8 ($\rho = 0.5$)
WER (%)	_	16.36	15.92	13.06
nave	61	575	111	117
nello	9	492	42	50
what	591	890	1067	764
ney	6212	6132	6306	6230
aught	0	1	102	23
nah	0	42	133	4
ne	0	15	98	3
he	1081	1203	1279	1184
what's	498	561	609	562
inna	0	13	55	5