Natural Speech Technology

Edinburgh – Cambridge – Sheffield

A General ANN Extension for HTK

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Abstract

- HTK-ANN enables ANNs with a general structure for acoustic modelling and feature extraction in HTK.
- Include recent ANN techniques, e.g., sequence training, stacking, speaker adaptation, and parameterised activation functions.
- Fully integrated to HTK, to reuse existing GMM-HMM methods for ANN-HMMs.
- HTK-ANN has been tested at CUED on data sets ranging from 3 to 1,000 hours and will be released as part of HTK 3.5 in 2015.

Design Principles

- To accomodate new models and methods, HTK-ANN should be designed should be as generic as possible
  - Flexible input feature configurations.
  - Generic ANN model architectures.
- HTK-ANN should be compatible with existing HTK functions
  - To minimise the effort to reuse previous source code and tools.
  - To simplify the transfer of many technologies.
- HTK-ANN should be "research friendly".

Generic ANN Support

- Each ANN can have any number of layers.
  - The input vector to an ANN layer is defined by a *feature mixture*.
  - Each feature mixture has any number of *feature element*.
  - A feature element defines a fragment of the input vector by *source* (acoustic features or ANN layers) and *context shift set* (integers for time difference).
- ANNs can be any directed cyclic graph (recurrent ANNs) but only directed acyclic graphs (feedforward ANNs) can be trained now.

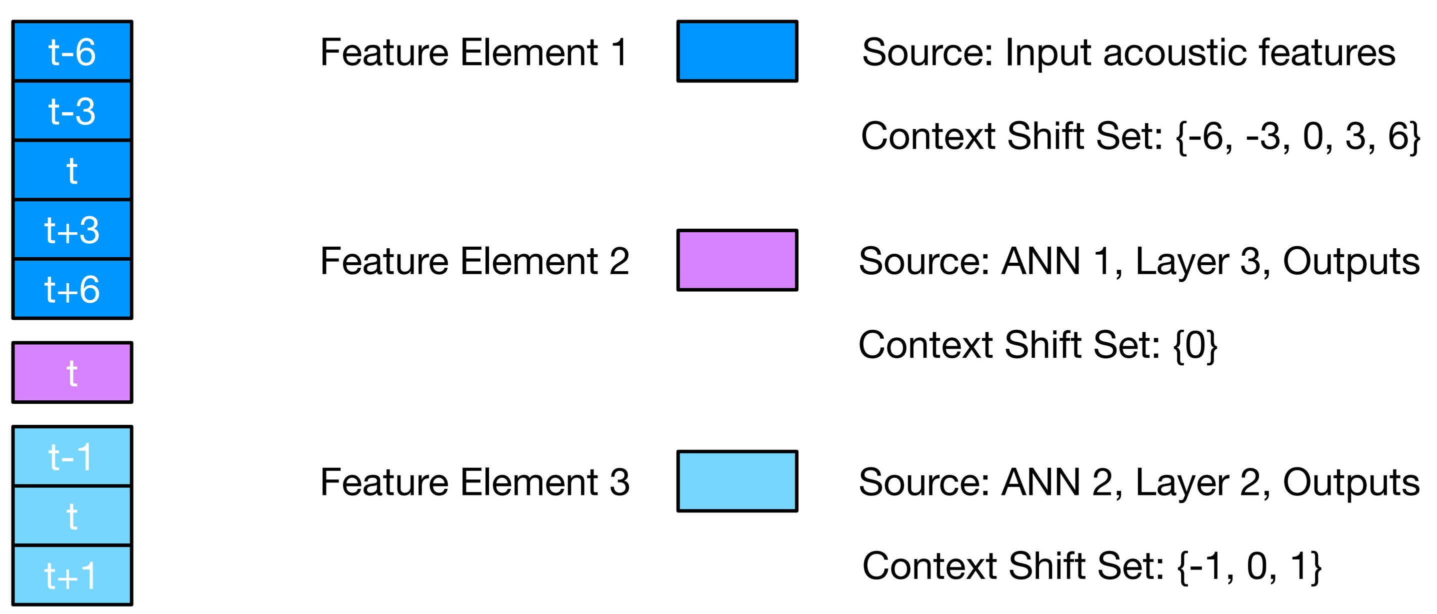

Figure: An example of a feature mixture

ANN Training Facilities

- HTK ANN has both frame level (CE, MMSE) and sequence level (MMI, MPE) training criteria.
- ANN labels come from frame-to-label alignment (for CE & MMSE), feature files (for autoencoder), and lattice files (for MMI & MPE).
- Only standard EBP with SGD is available at present.
  - Gradient refinement: momentum, graident clipping, weight decay, *etc.*
  - Learning rate schedulers: List, Exponential Decay, Ada Grad, modified New Bob, *etc.*

Data Cache

- Frame based shuffling: CE/MMSE for DNN and (unfolded) RNN.
- Utterance based shuffling: MMI, MPE, and MWE training.
- Batch of utterance level shuffling: RNN, ASGD.

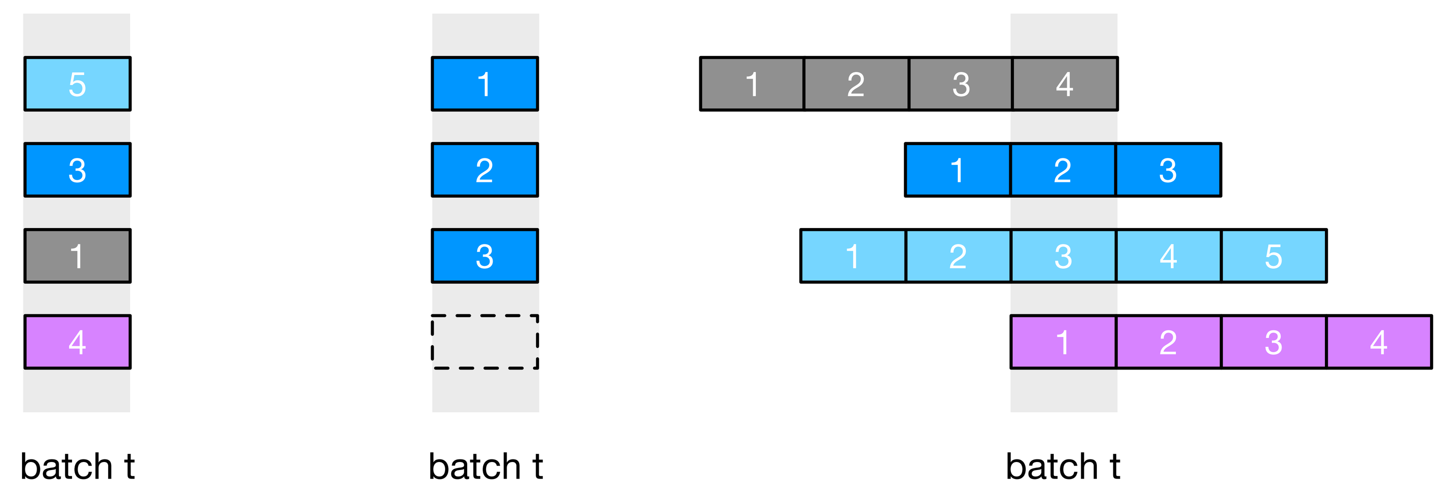

Figure: Examples of different types of data shuffling

Other Features

- Math kernels: CPU, MKL, and CUDA based new kernels for ANNs.
- Input transforms: compatible with HTK SI/SD input transforms.
- Speaker adaptation: an ANN parameter unit online replacement.
- Model Edit (using HHEd)
  - Insert/Remove/Initialise an ANN layer
  - Add/Delete a feature element to a feature mixture
  - Associate an ANN model to HMMs
- Decoders
  - HVite: tandem/hybrid system decoding/alignment/model marking
  - HDecode: tandem/hybrid system LVCSR decoding
  - HDecode.mod: tandem/hybrid system model marking
  - Joint decoder: log-linear combination of HTK systems (based on the same decision tree).

Building Hybrid SI System

- Steps of building CE based SI CD-DNN-HMMs using HTK
  - Produce desired tied state GMM-HMMs by decision tree tying (HHEd).
  - Generate ANN-HMMs by replacing GMMs with an ANN (HHEd).
  - Generate frame-to-state labels with a pre-trained system (HVite).
  - Train ANN-HMMs based on CE (HNTrainSGD).
- Steps for CD-DNN-HMM MPE training
  - Generate num. & den. lattices (HLRescore & HDecode).
  - Phone mark num. & den. lattices (HVite or HDecode.mod).
  - Perform MPE sequence training (HNTrainSGD).

ANN Front-ends for GMM-HMMs

- ANNs can be used as GMM-HMM front-ends by using a feature mixture to define the composition of the GMM-HMM input vector.
- HTK can accomodate a tandem SAT system as a single system.
  - Mean & variance normalisations are treated as activation functions.
  - SD parameters are replaceable according to speaker ids.

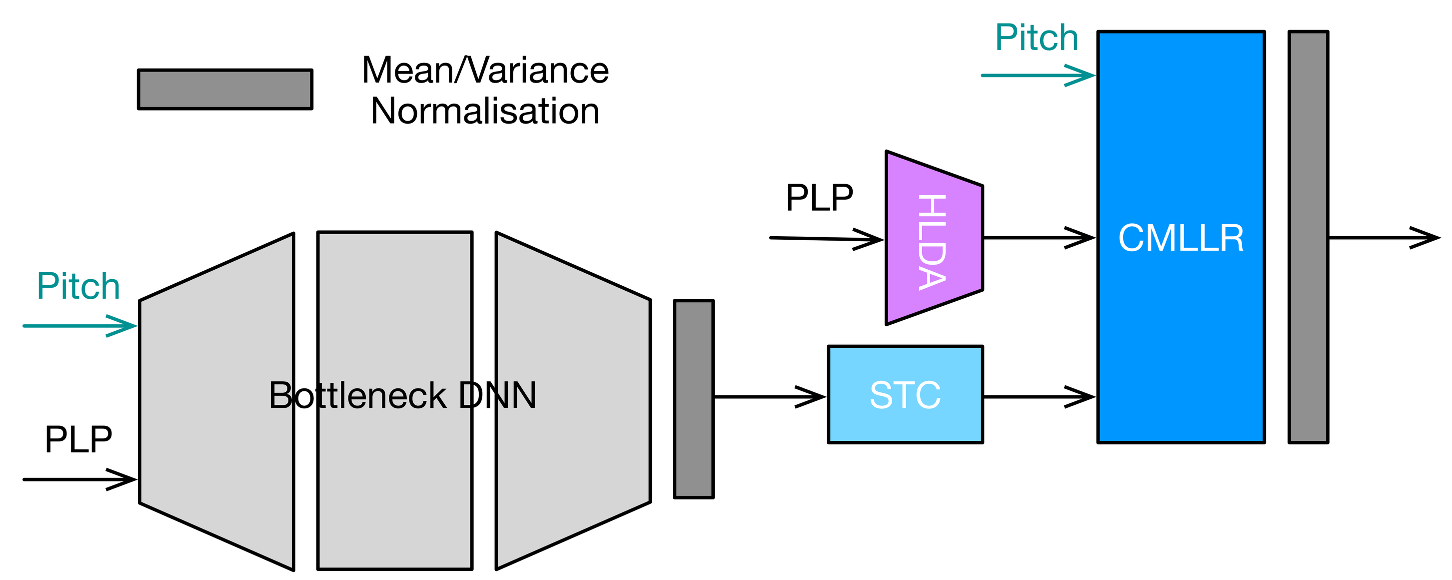

Figure: A composite ANN as a Tandem SAT system front-end

Experiments

- Systems were trained on 200 hours NST MGB Challenge Data and evaluated on BBC 1week development set (manual segmentation).
- DNNs are with 1k node hidden layers and 6k node output layers.

System	Criterion	%WER
Hybrid SI	CE	32.0
Hybrid SI	MPE	28.8
Tandem SI	MPE	29.7
Hybrid SI $\otimes$ Tandem SI	MPE	27.6

Table: *Tandem and hybrid system performance.*