HTK Version 3.4 Features (cont)

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HTK Large Vocabulary Decoder - HDecode

• Basic Features:

- bi-gram or tri-gram full decoding
- lattice generation
- lattice rescoring and alignment
- Supporting many other HTK Features:
 - fully integrated with adaptation schemes
 - STC and HLDA
 - lattice generation for discriminative training
- Typical use in a multi-pass system
- Limitations and Future Development



HDecode: Basic Features (1)

- Tree strutured network based beam search cross-word trip-hone decoder.
- Effective pruning techniques to constrain search space:
 - main search beam
 - word end beam
 - maximum active model
 - lattice beam
 - LM back-off beam
- Efficient likelihood computation during decoding:
 - state and/or component output probability caching
 - language model probability caching
- Token sets merging and LM score look-ahead during propagation



HDecode: Basic Features (2)

HDecode performs search using a model level network expanded from a dictionary and a finite state grammar constructed from a word based bi-gram or tri-gram model, as in *full decoding*:

- 1-best transcription stored in HTK MLF format.
- word lattices may be generated in HTK SLF format with
 - detailed timing
 - word level scores (acoustic, LM and pron)
 - LM and pron prob scaling factors
 - other model specific information
- Higher order N-gram models applicable to resulting lattices (HLRescore).



HDecode: Basic Features (3)

or word lattices marked with LM scores, as in *lattice rescoring*.

- HDecode outputs "word lattices" containing duplicate word paths of
 - different pronunciation variants "contrapoint"
 - silence related different phone contexts "fugue"
- **determinization** of word lattices required prior to rescoring (HLRescore).
- 1-best hypothesis and lattices generated as in full decoding.
- model level alignment may also be generated in resulting lattices:
 - model alignment and duration marked on lattice arcs
 - important for discriminative training



HDecode: Supported new HTK Features

- A variety forms of linear transformations for adaptation:
 - MLLR transforms
 - CMLLR transforms
 - covariance transforms
 - hierarchy of linear transformations
- Covariance modeling and linear projection schemes:
 - STC
 - HLDA
- Lattice generation for discriminative training:
 - denominator word lattices generation
 - numerator and denominator lattices model alignment



HDecode: Typical use in a multi-pass system

- Upadapted tri-gram decoding plus 4-gram rescoring to generate initial hypotheses with tight pruning.
- Bi-gram or tri-gram adapted full decoding to generate word lattices with wide pruning.
- Lattice expansion and pruning using more complicated LMs (HLRescore).
- Lattice rescoring using re-adapted more complicated acoustic models and system combination.





HDecode: Limitations and Future Development

- Known limitations are:
 - only works for cross-word tri-phones;
 - sil and sp symbols reserved for silence models;
 - appended to all words in pronunciation dictionary;
 - lattices generated require determinization for rescoring;
 - only batch mode adaptation supported.
- Possible future work areas:
 - fast Gaussian likelihood computation?
 - more efficient token pruning?
 - incremental adaptation?



HTK Discriminative Training Tools

• Basic Features:

- MMI
- MPE and MWE
- efficient lattice based implementation

• Supporting many other HTK Features:

- fully integrated with adaptation schemes
- discriminative MAP
- lattice based adaptation
- single pass re-train using new front-ends

• Typical procedure of building discriminatively trained models



HTK Discriminative Training Tools: Training Criteria

Two types of discriminative training criteria supported:

• maximum mutual information (MMI)

$$\mathcal{F}(\lambda) = \sum_{r} \log P(\mathcal{W}^{r} | \mathcal{O}^{r}, \lambda)$$

• minimum Bayes risk (MBR)

$$\mathcal{F}(\lambda) = \sum_{r, \tilde{\mathcal{W}}} P(\tilde{\mathcal{W}}^r | \mathcal{O}^r, \lambda) \mathcal{A}(\mathcal{W}, \tilde{\mathcal{W}})$$

with error cost function $\mathcal{A}(\mathcal{W},\tilde{\mathcal{W}})$ computed on

- phone model level *minimum phone error* (MPE)
- word level minimum word error (MWE)

HTK Discriminative Training Tools: Basic Procedure





HTK Discriminative Training Tools: I-smoothing

Flexible use of prior information for parameter smoothing:

- Common priors used in I-smoothing:
 - ML statistics
 - MMI statistics
 - Static model based priors
 - hierarchy of smoothing statistics back-off
 - important for MPE/MWE training to generalize well
- Applicable to a variety of systems:
 - useful in discriminative MAP training
 - gender dependent HMMs
 - cluster adaptively trained HMMs (CAT)
 - STC/HLDA models



HTK Discriminative Training Tools: Lattice Implementation

Two sets of model marked lattices required:

- *numerator* lattices: from reference transcription
- **denominator** lattices: from full recognition using weak LM

Efficient lattice level forward-backward algorithm benefits from:

- support of flexible sharing of model parameters
- state and Gaussian level output probability caching
- Gaussian frame occupancy caching
- fixed phone boundary model internal re-alignment "Exact Match"
- batch I/O access of lattices as merged lattice label files (LLF)



HTK Discriminative Training Tools: Std Configurations

Useful common configuration variables:

- E: constant used in EBW update, e.g., 2.0
- LATPROBSCALE: acoustic scaling by LM score inverse, e.g., 1/13
- ISMOOTH{TAU, TAUT, TAUW}: I-smoothing constants, e.g., 50/1/1 for MPE
- PRIOR{TAU, TAUT, TAUW, K}: static prior, e.g., 25/10/10/1, for MPE-MAP
- PHONEMEE: MWE or MPE training
- EXACTCORRECTNESS: "Exact" or approximate error in MPE/MWE
- MMIPRIOR: use MMI prior



HTK Discriminative Training Tools: Supported HTK Features & Limitations

Many other useful HTK features are supported:

- multi-streams, tied-mixtures and parameter tying
- $\bullet\,$ a variety of adaptation schemes, e.g., MMI/MPE-SAT
- lattice based adaptation
- single pass re-train using new front-ends, e.g., bandwidth specific models Know limitations are:
- only diagonal covariance HMMs supported
- Gaussian means and variances tied on the same level



HTK Discriminative Training Tools: General procedure





Thank you!

