Incremental Unsupervised Training for University Lecture Recognition

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The KIT Lecture Translation System

- University lectures are often given in the local language
- At KIT, lectures in German language are a significant obstacle for foreign students
- How to bridge the language barrier?
  - Human interpreters for translations are too expensive
  - Spoken language translation (SLT) systems provide an affordable solution

The KIT Lecture Translation System

- One of KIT's current research focuses is the automatic translation of university lectures to
  - aid foreign students
  - bring simultaneous speech translation technology into lecture halls
- Lecture translator as combination of *speech-to-text* (STT) and *statistical machine translation* (SMT) system
  - STT performance is critical
  - Crucial: Tailoring system's models to lecturer's speech and topic

Objective of this Work

- Training and adaptation to new lectures, topics, speakers, environments is necessary
  - Acoustic model (AM) adaptation
  - Language model (LM) adaptation (not topic of this work)

- New lecture related audio data is generated periodically
- Manual transcription and training is expensive and time consuming

Objective of this Work

- Proposal: Unsupervised adaptation of the acoustic model to specific speakers
  - Retraining the AMs is possible every time new data is available
  - A system an be optimized *during* a term, and not only at the end
- Approach: Producing automatic transcriptions of new lectures with a speaker independent system and exploiting these for improving the system
  - Re-training AM by performing one additional iteration of Viterbi training

Objective of this Work

- Training in dependency of the amount of training data
- No closely related texts available for any kind of supervision
- Treatment of pronunciation variants and noise words during re-training
  - Transcriptions deliver detailed informations
- Filtering of erroneous data and garbage is done by use of
  - State confidence scores on word level
  - Thresholding & weighting by word posterior confidence scores

Experimental Set-up
Training & Test Data

- SI system was trained on 94 hours of KIT lecture corpus data
- Adaptation experiments constrained to 2 distinct speakers

	trainSet	testSet
Speaker A	444 min	29 min
Speaker B	498 min	39 min

- trainSets have never been seen by the SI system
- testSets come from different lectures than the remaining data

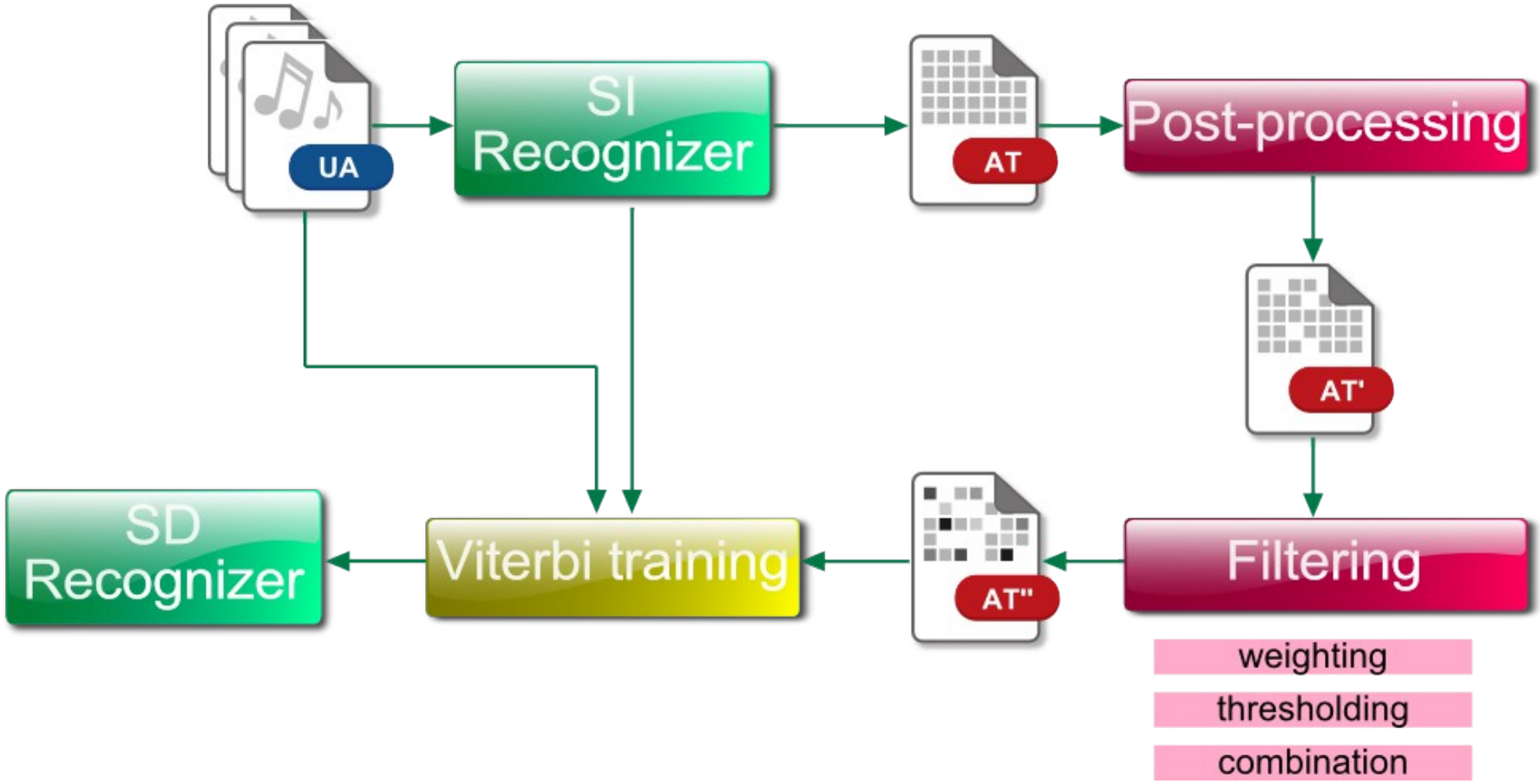
Baseline System

- Speaker independent German lecture translation system
  - 4000 generalized quinphone models, 3 state left-to-right HMMs
  - MVDR front-end, frame-stacking, VTLN
  - 4-gram LM, trained on sources like web dumps, news, transcripts

- Baseline performance (in WER)
  - SD system for speaker A trained in a supervised fashion

	SI	SD
Speaker A	19.7%	17.3%
Speaker B	34.8%	---

Unsupervised Adapation
Framework



Pronunciation Variants & Noises

- Four different degrees of transcription post-processing

recognition	unmodified decoder output
	$(<noise>) also(1) wenn(1) wir(6) $(<breath>) hier
baseWords	words mapped to base forms
	$(<noise>) also wenn wir $(<breath>) hier
baseAll	+noise mapped to base forms
	$ also wenn wir $ hier
filtered	plain text
	also wenn wir hier

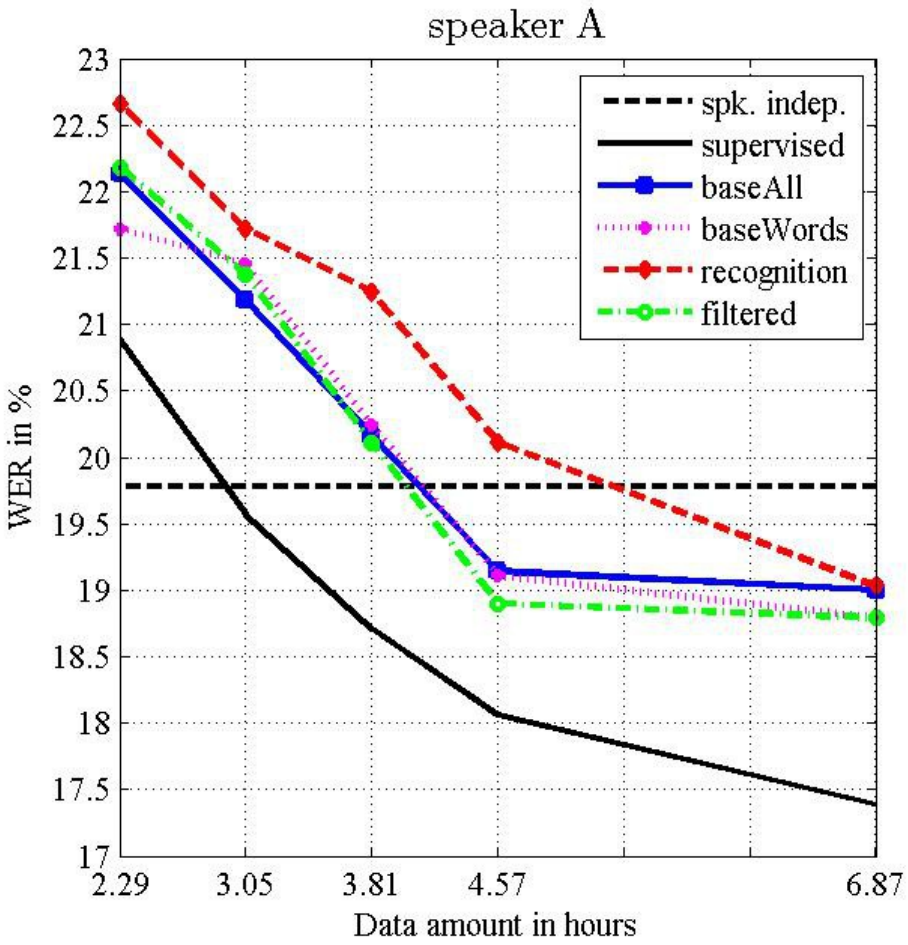
Pronunciation Variants & Noises

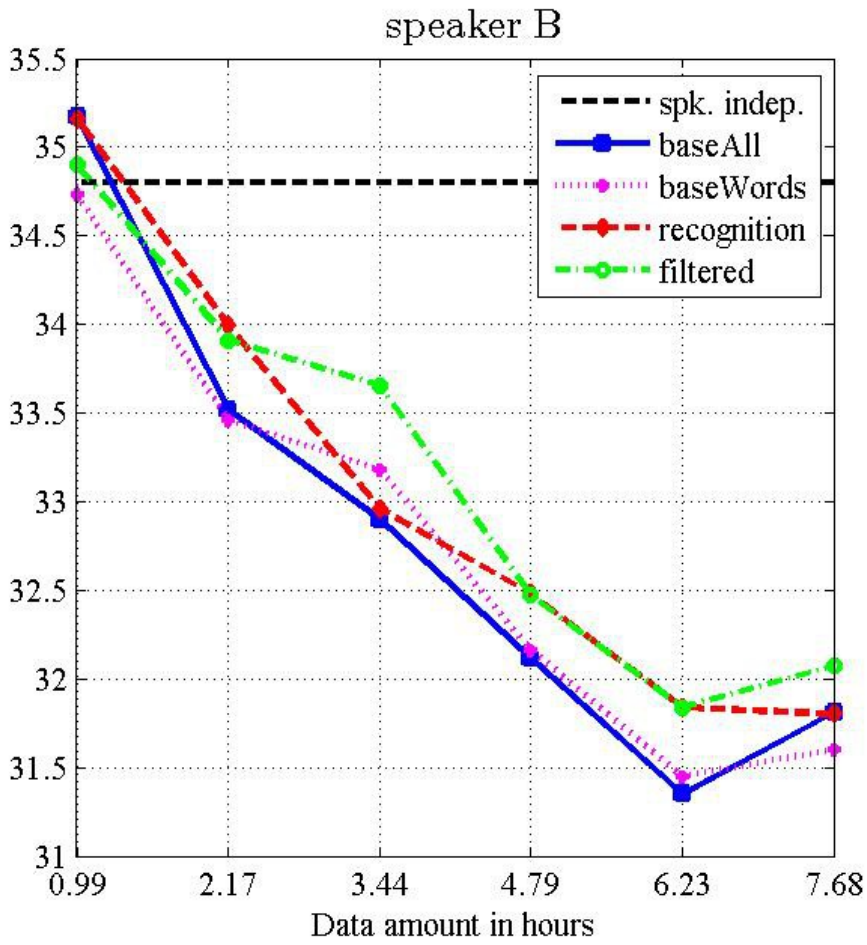
- Janus allows modifications on the hypothesis during label writing
- During label writing, the decoder
  - choses the most probable variant of a word
  - autonomously inserts optional words (optWords, marked as $)
- General assumption: With more detail in the transcriptions, the label writing process can react more dynamically to difficult or noisy parts

baseAll	*$ also wenn wir $ hier*
	$ $ $ also(1) $ wenn $ wir(2) $ $ $ hier $

Unsupervised Adapation

Pronunciation Variants & Noises





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Unsupervised Adapation

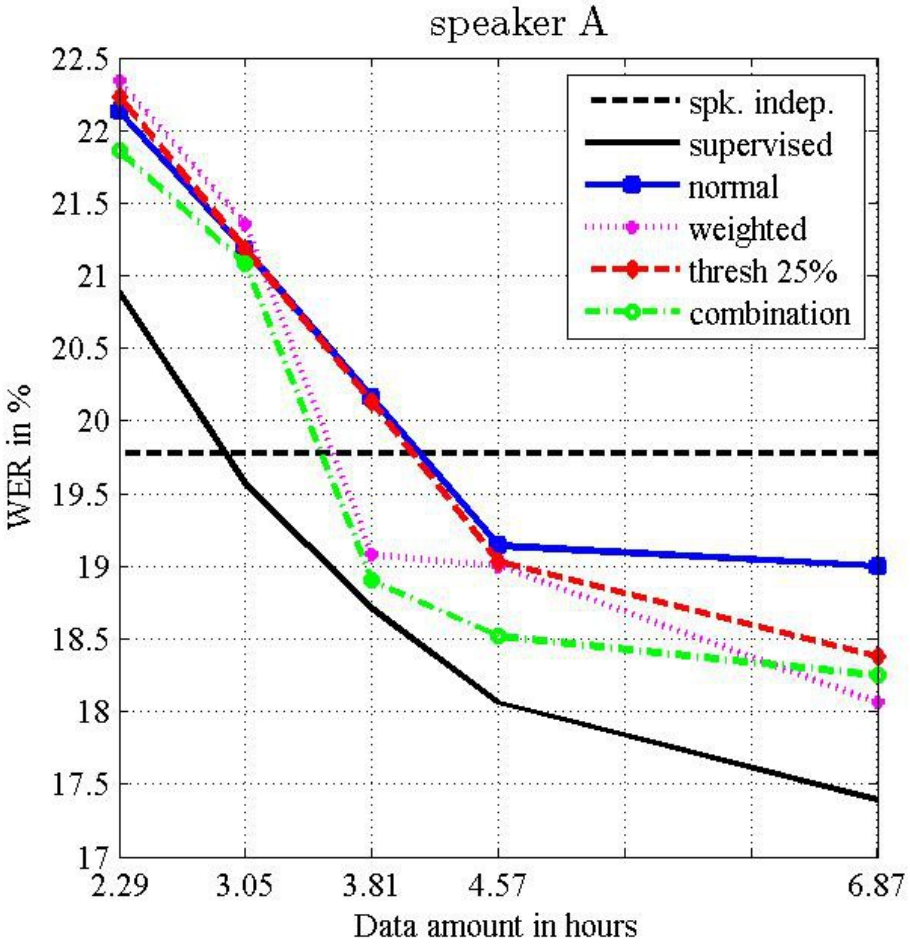
Confidence Weighting & Thresholding

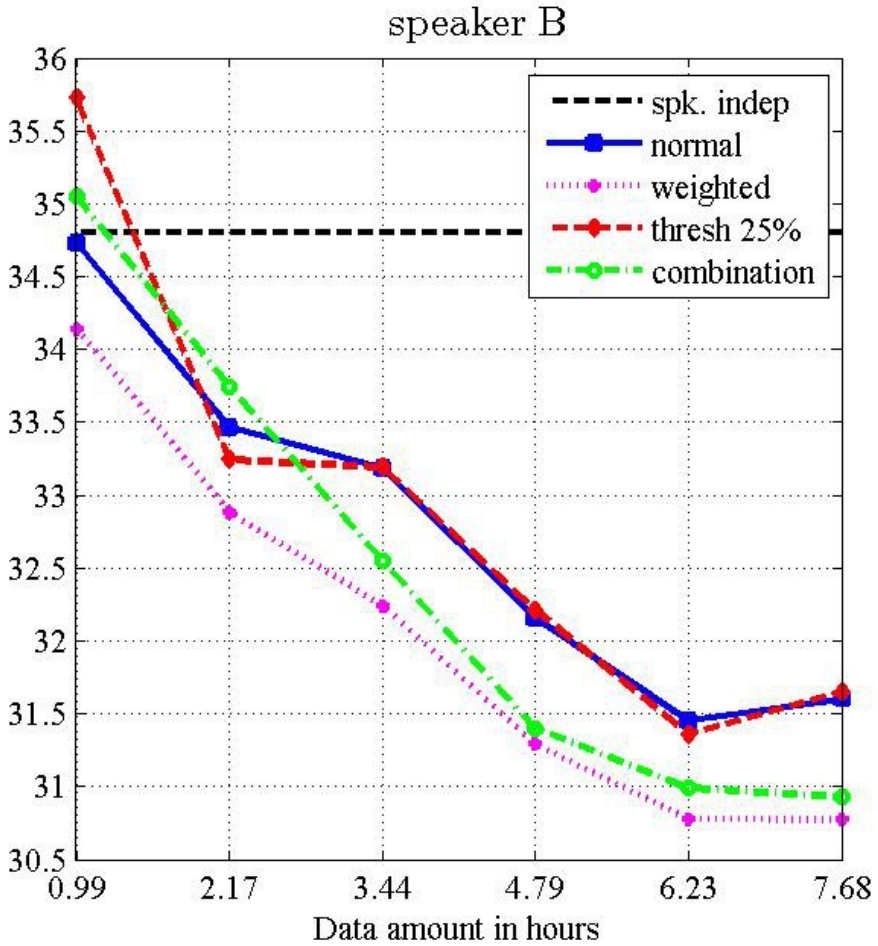
- Word level posterior probabilities from decoding as confidence scores
- Utilization for word based weighting & thresholding

weighting	word based weighting during training
	also(1)$^{0.73}$ wenn(1)$^{0.89}$ wir(6)$^{0.35}$ $(<breath>)$^{1.0}$ hier$^{0.46}$
thresholding	word based filtering by a confidence threshold
	also(1) wenn(1) wir(6) $(<breath>) hier
combination	combined weighting and thresholding
	also(1)$^{0.73}$ wenn(1)$^{0.89}$ wir(6) $(<breath>)$^{1.0}$ hier

Unsupervised Adapation

Confidence Weighting & Thresholding





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Conclusion

- Automatic transcriptions of new lectures using SI system
  - Unsupervised training for improving this system to specific lecturers
- Post-processing
  - Viterbi algorithm during training makes better decisions regarding pronunciation variants and noise insertions
  - Given low base performance, additional information in transcriptions helps
  - Given a good base performance, filtered transcriptions are advantageous
  - Viterbi training needs a certain amount of data to succeed (> 1 hour)
- Confidence score utilization
  - Weighting is always beneficial
  - Thresholding can support weighting

Thank you!