Adam Mickiewicz University in Poznań
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Automatic error correction in ASR

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Outline

1 About me

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3 Related work

4 A Spelling Correction Model For End-to-end Speech Recognition
- Motivation
- Dataset
- Method
- Evaluation

5 Tagging approach

About me

- Tomasz Ziętkiewicz
- tomasz.zietkiewicz (at) amu.edu.pl
- PhD Student at "Applied Doctorate" studies
- Work at Samsung R&D Poland
- Area of work & research:
  - Automatic Speech Recognition post-processing
  - Inverse Text Normalization
  - Automatic correction of ASR errors
  - Sequence labeling
  - Sequence-to-sequence methods

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Problem definition

Given corpus of hypothesis from Automatic Speech Recognition system and corresponding reference utterances, learn a transformation from the former to the latter

Rationale

Why such transformation is needed? It can be used in ASR system as postprocessing stage as:

- re-scoring of hypothesis produced by ASR using information not present at earlier stages of processing (i.e. one directrional LM)
- adaptation of a black box, general domain ASR system to some specific domain

Outline

Related work

- Cucu, Horia, Andi Buzo, Laurent Besacier, and Corneliu Burileanu, 2013. „Statistical Error Correction Methods for Domain-Specific ASR Systems"
- Luis Fernando D'Haro, Rafael E. Banchs, „Automatic Correction of ASR outputs by Using Machine Translation", Interspeech 2016
- Jinxi Guo, Tara N. Sainath, Ron J. Weiss „A Spelling Correction Model For End-to-end Speech Recognition"

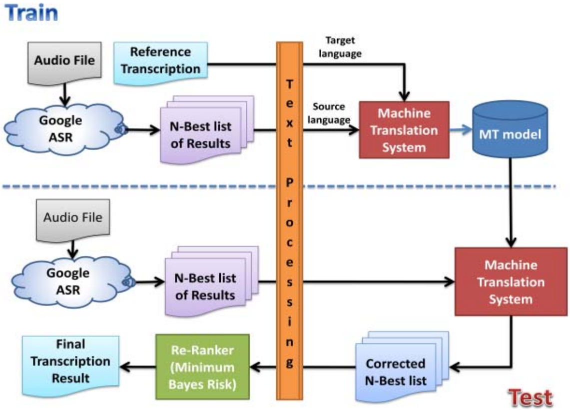
Statistical Error Correction Methods for Domain-Specific ASR Systems

- error correction using SMT (Statistical Machine Translation) model.
- trained on relatively small parallel corpus
- 2000 ASR transcripts and their manually corrected versions.
- At evaluation time the model is used to “translate” ASR hypothesis into it’s corrected form.
- Results: 10.5% relative WER improvement by reducing the baseline ASR system’s WER from 11.4 to 10.332 .

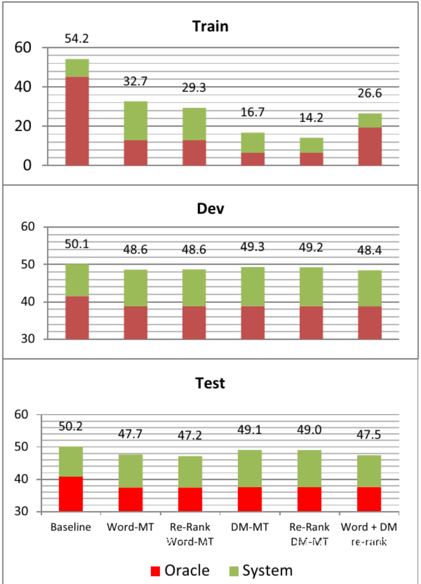
Automatic Correction of ASR outputs by Using Machine Translation

- Phrase-based machine translation used on reference sentences and n-best list of hypothesis from ASR
- Uses Minimum Bayes Risk re-ranker to choose among translated entries from n-best list

Automatic Correction of ASR outputs by ... System architecture



Automatic Correction of ASR outputs by ... - Results



Outline

A SPELLING CORRECTION MODEL FOR END-TO-END SPEECH RECOGNITION

Jinxi Guo[1*] , *Tara N. Sainath*[2], *Ron J. Weiss*[2]

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Motivation

- Popularity of end-to-end ASR models
- Acousting, pronunciation and language model combined in one neural network
- Problem: needs annotated audio data
- LM trained on small dataset compared with "traditionaląpproach
- Worse performance on rare words

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Possible solutions

- Incorporating external LM trained on text-only data
  - Rescoring n-best decoded hypothesis from end-to-end ASR
  - Incorporate RNN-LM into first-pass beam search by shallow, cold or deep fusion
- Rare words and proper nouns are still problematic with this approach
- Why?
- LM trained with other objective then correcting e2e model's errors

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Solution

Proposed solution: spelling corrector model on text-to-text (hypothesis-to-refrerence) pairs.

Dataset

- LibriSpeech
- Large-scale (1000 hours) corpus of read English speech
- audiobooks from the LibriVox project
- carefully segmented and aligned
- http://www.openslr.org/12/
- License: CC BY 4.0

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Baseline

- LAS - Listen Attend and Spell
- Encoder-decoder with attention

Spelling correction model

- attention-based encoder-decoder sequence-to-sequence

Architecture

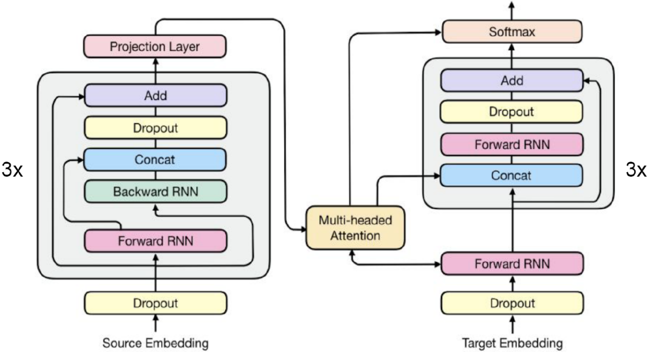


Fig. 1. Spelling Correction model architecture.

Results

System	Dev-clean	Test-clean
LAS	5.80	6.03
LAS $\rightarrow$ LM (8)	4.56	4.72
LAS-TTS	5.68	5.85
LAS-TTS $\rightarrow$ LM (8)	**4.45**	**4.52**
LAS $\rightarrow$ SC (1)	5.04	5.08
LAS $\rightarrow$ SC (8) $\rightarrow$ LM (64)	**4.20**	**4.33**
LAS $\rightarrow$ SC-MTR (1)	4.87	4.91
LAS $\rightarrow$ SC-MTR (8) $\rightarrow$ LM (64)	**4.12**	**4.28**

Table 1. Word error rates (WERs) on LibriSpeech "clean" sets comparing different techniques for incorporating text-only training data. Numbers in parentheses indicate the number of input hypotheses considered by the corresponding model.

Results

System	Dev-clean	Test-clean
LAS	3.11	3.28
LAS $\rightarrow$ SC (1)	3.01	3.02
LAS $\rightarrow$ SC (8)	**1.63**	**1.68**

Table 2. Oracle WER before and after applying the SC model.

Results

System	Dev-clean	Dev-TTS
LAS baseline	5.80	5.26
LAS $\rightarrow$ SC (1)	5.04	**3.45**
LAS $\rightarrow$ SC (8) $\rightarrow$ LM (64)	4.20	**3.11**

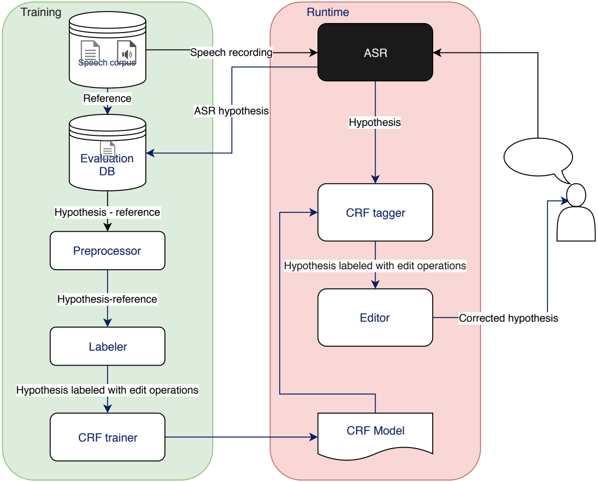
Table 3. WER comparison on a real audio and TTS dev sets.

Outline

Edit operations tagger approach

- Train
  - Compare ASR hypothesis and reference sentences from parallel corpora
  - Extract pre-defined edit operations from the comparison
  - Create corpora with ASR hypothesis tagged with edit operations labels
  - Train a tagger using this corpora
- Test
  - Use tagger on ASR hypothesis
  - Apply edit operation to the hypothesis

Architecture



Example

Reference: "Multimodal distribution"
Hypothesis: "Multi modal distribution"
Tagged hypothesis:

Word	Tag
Multi	join
modal	None
distribution	None

Edit operations tagger approach

- Pros
  - Safe - Default operation - do nothing
  - Easy to control - filter operation using tag score treshold
  - Set of used edit operations can be adjusted to fix only specific kind of errors
- Cons
  - Need to manually define edit operations
  - Need to implement edit operations deducer
  - Set of operations is limited due to performance constraints

Implementation

- Current implementation: Conditional Random Fields (CRF) tagger
  - Handcrafted features: prefix, suffix, length, left context, right context
  - CrfSuite library
  - Number of edit operations limited to 200 most popular ones
- Planned implementation: Neural tagger using RNNs/LSTMs

Thank you

Thank you for your attention!