FIX IT WHERE IT FAILS: PRONUNCIATION LEARNING BY MINING ERROR CORRECTIONS FROM SPEECH LOGS

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ICASSP (2015) – 2015 IEEE International Conference on Acoustics, Speech and Signal

Processing (ICASSP)

Date of Conference: 19-24 April 2015

Page(s): 4619-4623

DOI: <u>10.1109/ICASSP.2015.7178846</u>

OVERVIEW

- Automatic speech recognition (ASR) systems include a pronunciation dictionary (or lexicon) and a grapheme to phoneme (G2P) engine
 - The lexicon consists of word-pronunciation pairs written by linguist
 - · Hand-generated cannot keep up with growing vocabulary
 - · G2P has limited accuracy
 - · Proper names pronunciation can be influenced by historical or foreign-origin factors
- Speech recognition task in general finds the word sequence that has the maximum posterior probability given the acoustic observations
 - · Relies heavily on a lexicon
 - · Uses a G2P for words not found in the lexicon

A maximum a posteriori probability (MAP) estimate is a mode of the posterior distribution.

The **posterior probability** of a random event or an uncertain proposition is the conditional probability that is assigned after the relevant evidence or background is taken into account. Similarly, the **posterior probability distribution** is the probability distribution of an unknown quantity, treated as a random variable, conditional on the evidence obtained from an experiment or survey.

"Posterior", in this context, means after taking into account the relevant evidence related to the particular case being examined.

EXISTING/RELATED WORK

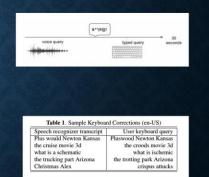
- · Research on machine learning for G2P conversion:
 - Decision tree classifier to learn pronunciation rules
 - · Joint ngram model
 - · Maximum entroy model
 - · Active learning
 - · Recurrent neural network
- Studies on detection speech recognition errors:
 - · Using acoustic and prosodic features to identify corrections
 - · Prosodic features to detect recognition errors
 - · Examining features related to the user's speaking style to detect speech errors
 - Decision-tree based method to detect voice query retires
 - · Co-occurence method for detecting and correcting misrecognition

NEW APPROACH

- Correction data focuses specifically on the areas of weaknesses of the system
 - · Do not need to identify bad pronunciations ahead of time
- Language-independent
- Corrections are provided by the users who spoke them, who know how they want to pronounce the words
- Using two different types of correction data:
 - Keyboard Correction
 - Selected Alternate

KEYBOARD CORRECTION DATA

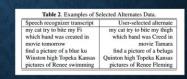
- · User makes a voice query, then issues a typed query shortly after
 - · Within 30 seconds
- Analysis showed only 30-40% of these pairs are true corrections
- · Correction data classifier features
 - · Word-based:
 - Unigram counts, number of word overlaps, and language model costs
 - · Character-based:
 - Character counts, and edit distance between the recognized and typed queries
 - · Phoneme:
 - Counts and edit distance between the phoneme sequences corresponding to the recognition results and typed query
 - Acoustic:
 - · Forced phone alignment costs
 - Waveform-to-transcript length ratio



SELECTED ALTERNATE DATA

- Google voice search user interface allows users to manually select from a list of alternative recognition results
- User selection provides a high quality correction, so no extra classifier needed





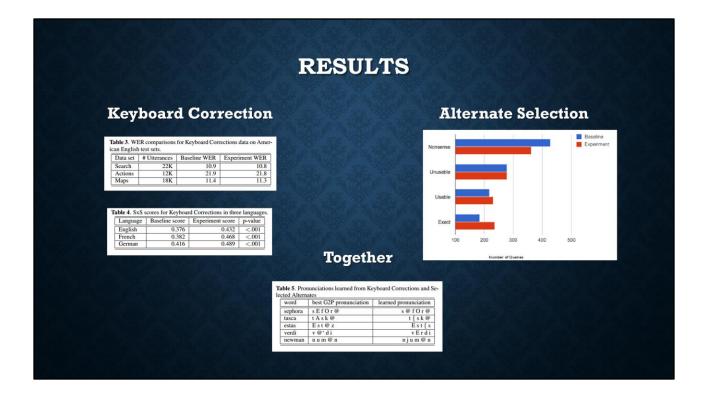
TESTING

- Word error rate (WER) evaluation:
 - · Anonymized speech queries randomly selected from traffic logs and human-transcribed
 - The most frequently used words already have a good pronunciation, but are still useful to ensure no learned "roque" pronunciations
- Side-by-side (SxS) tests:
 - · Two ASR engines: one with the learned pronunciations and one without
 - · Both engines are fed the exact same queries from anonymized voice search logs
 - Queries with differing recognition transcripts are evaluated by human raters and marked as one of four categories:
 - · Nonsense: the transcript is nonsense
 - Unusable: the transcript does not correspond to the audio
 - · Usable: the transcript contains only small errors
 - · Exact: the transcript matches the spoken audio exactly

WER: phone sequence for an infrequent word that matches the pronunciation of a different and more frequent word that would now be mirecognized

SxS: Acoustic model, language model, and vocabulary are the same in both engines. Only the lexicon changes.

SxS experiments have the advantage of focusing on cases where pronunciation changes do affect the recognition results. They typically show more "movement" than WER measurements on fixed test sets.



An experiment is considered positive if its SxS score is higher than that of the corresponding baseline. Generally this means it has fewer nonsense/unusable queries and more usable and exact queries.

Keyboard Correction:

We see a small reduction in word error rate on each test set.

SxS score improvements from adding new pronunciations to the baseline ASR engine

Alternate Selection:

The amount of data flowing through the Alternate Selection pipeline is smaller than that from Keyboard Corrections. As a result, the system learns fewer pronunciations, and our experiments showed no impact on standard test set word error rates. However, SxS evaluations showed significant improvements.

Side-by-side experiments demonstrate that the pronunciations learned via our methods significantly improve the quality of a production-quality speech recognition system.

