Using Spoken Word Posterior Features in NMT

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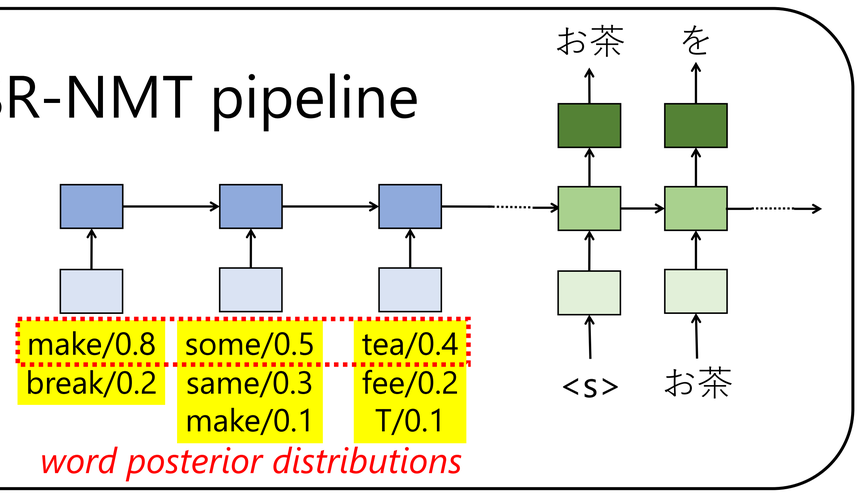
Quick summary

Use *word posterior distributions* as NMT inputs in SLT by ASR-NMT pipeline

- Handle ASR ambiguity using word posterior distributions
- Train with both 1-hot (text) and distributional (ASR) inputs
- Improvements over a simple cascade with ASR 1-bests
  - 4-5 pts. BLEU gains on BTEC (synthesized) and ATR-English (natural)



Problem & previous approaches

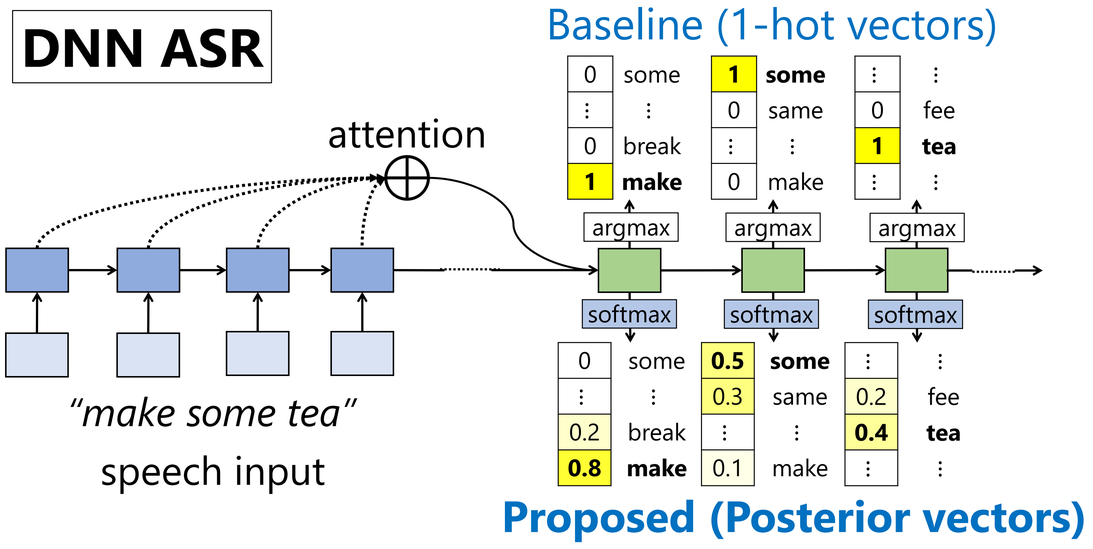
ASR error propagation (well-known!)

- Lattice-based integration [Su+ 2017, Sperber+ 2017 (also many such studies by SMT)]
  - Complex implementation/computation
- Direct network integration [Berard+ 2016, Kano+ 2017]
  - Works poorly in English-Japanese

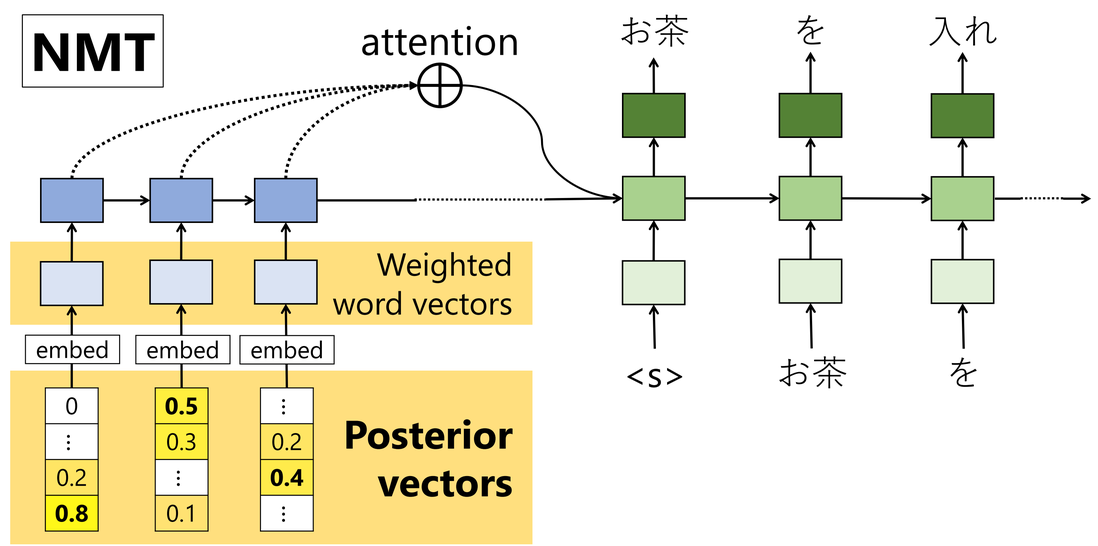
Proposed method

Integration based on word posterior

1. Obtaining word posterior distributions from the *softmax* layer of an ASR decoder



2. Using the posterior distributions as inputs to an NMT decoder (i.e. using weighted word embeddings)



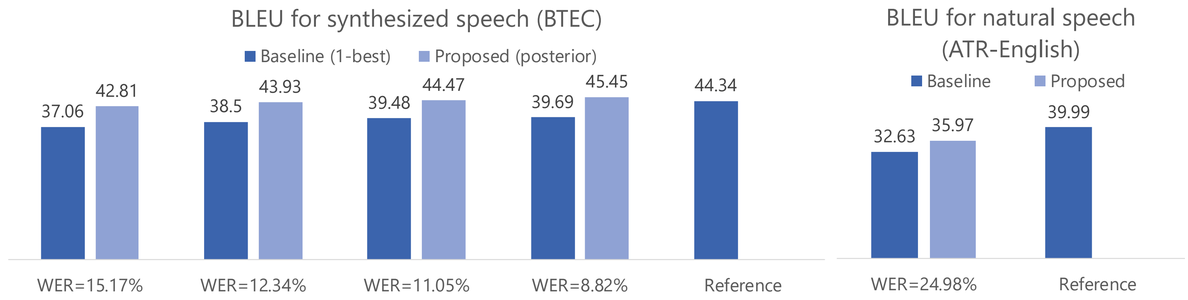
Advantages

- Simple integration by small modifications to existing ASR & NMT implementations
- Straightforward combination of text- and ASR-based NMT training
  - Pre-training with 1-hot text inputs
  - Fine-tuning with ASR posteriors

Experimental results

Consistent improvements over 1-best

- Outperformed text-NMT with low-WER!?



- ASR error recovery by word posterior
  - R: Excuse me where is the closest ~~shoe~~ store
    station (0.439)
    shoe (0.321)
  - B: すみません一番近い**駅**はどこですか (station)
  - P: すみません一番近い**靴屋**はどこですか (shoe store)
- Resolving word confusion by ASR-aware embeddings even without ASR errors
  - R: I'd like to have a **perm** and a **haircut** please
  - B: **パーマ**と**パーマ**をお願いします (perm, perm)
  - P: **パーマ**と**カット**をお願いします (perm, haircut)

Conclusions

We could achieve simple but effective ASR-NMT integration by word posteriors

Future work: Joint training of ASR+NMT

J. Su et al. (2014), Lattice-based Recurrent Neural Network encoders for Neural Machine Translation, Proc. AAAI
M. Sperber et al. (2017), Neural Lattice-to-Sequence Models for uncertain inputs, Proc. EMNLP
A. Berard et al. (2016), Listen and Translate: A Proof of Concept for End-to-End Speech-toText Translation, Proc. NIPS
T. Kano et al. (2017), Structure-based Curriculum Learning for End-to-End English-Japanese Speech Translation, Proc. Interspeech