

Grounded Sequence to Sequence Transduction (Multi-Modal Speech Recognition)

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Imagine How-To Videos

Start by **loosening** each **bolt**. Then locate the jack and **lift** the **car**. Now you can **remove** the bolts and then the **wheel**.

First **undo** the **nuts**. Once that done, you can **jack** the **car**. Then withdraw the nuts completely so that you can **remove** the flat **tire**.

The image shows two film strips. The top film strip has six frames: 1. A close-up of a car wheel with a bolt being loosened. 2. A close-up of a car wheel with a bolt being loosened. 3. A person using a jack to lift the car. 4. A person using a jack to lift the car. 5. A person using a jack to lift the car. 6. A person using a jack to lift the car. The bottom film strip has six frames: 1. A close-up of a car wheel with a nut being removed. 2. A close-up of a car wheel with a nut being removed. 3. A close-up of a car wheel with a nut being removed. 4. A person using a jack to lift the car. 5. A person using a jack to lift the car. 6. A close-up of a car wheel with a nut being removed.

- Lots of potential for multi-modal processing & fusion
- For Speech-to-Text and beyond

Audio-Visual ASR vs Multi-modal ASR

- Traditional audio-visual ASR based on speakers' lip/ mouth movement
 - **Sub-phonetic synchronicity** required, fusion a problem
- Lip/ mouth information not always available in how-to videos
 - Humans are usually present, but often they "do things"
- Instead: fuse information at the **semantic level (words, ...)**

e.g. AVASR "Grid" Corpus



"How-To" Video



Multi-Modal MT – Example

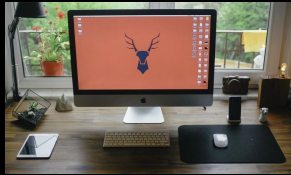


- ▶ **SRC**: Three children in **football uniforms** of two different teams are playing **football** on a **football field**, while another player and an adult stand in the background.
- ▶ **TXT**: Drei Kinder in **Fußballtrikots** zweier verschiedener Mannschaften spielen **Fußball** auf einem **Fußballplatz** während ein weiterer Spieler und eine Erwachsener im Hintergrund stehen.
- ▶ **IMG**: Drei Kinder in **Footballtrikots** zweier verschiedener Mannschaften spielen **Football** auf einem **Footballplatz** während ein weiterer Spieler und ein Erwachsener im Hintergrund stehen.

Courtesy of Lucia Specia

Two (+) Types of Features

- Object Features



- monitor, mouse, keyboard, ...
- 1000 classes [Deng et al., 2009]
- Could also do **Actions**, ...

- Place Features (Scenes)



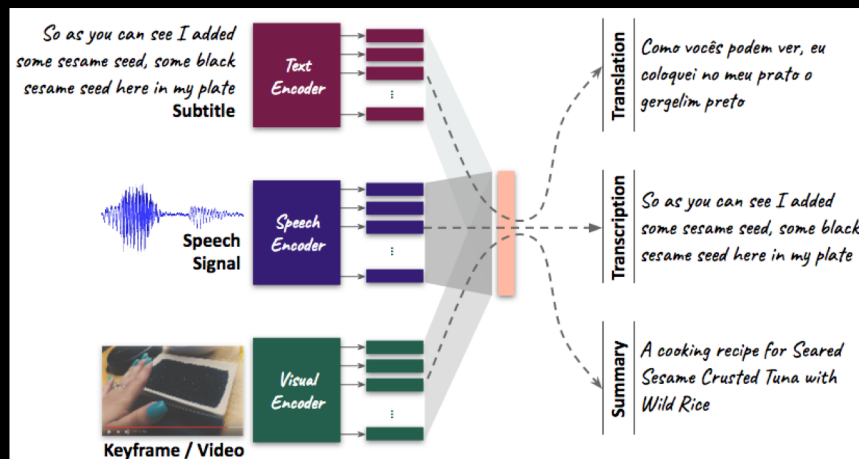
- train (office, baseball field, airport apron, ...)
- 205 classes [Zhou et al., 2014]

How-to Video Corpus [Miao et al., '14]

- "How-to" dataset of instructional videos
 - Harvested from the web (**2000h+ available**)
 - "Utterance" (from caption) is 8s...10s
 - On average 18 words
- ~55,000 videos
 - 300h+ have been translated into Portuguese
 - 4h dev & eval set; ~20k+ vocabulary size
- Extract one quasi-static visual "context" vector per utterance
 - Pick frame randomly (for now)
 - Object/ place detection, or action recognition



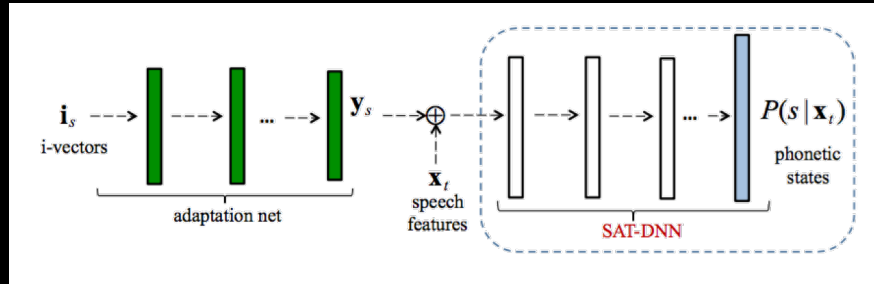
@ JSALT 2018: one NN to rule them all!



The Goal

- Have a corpus of 2000h of how-to videos
 - Fully transcribed in English
 - Partially translated into Portuguese (and Turkish)
 - With short descriptions of videos
- Learn shared audio-visual (or text-visual) representations to help us understand video
 - Recognize, translate, and summarize videos
- Use sequence-to-sequence models (S2S) as unified architecture

Preliminary Experiments: ASR Adaptation



- All is standard error back-propagation
- Independent of the structure & features, context
 - SAT technique can be naturally applied to CNNs, RNNs
 - Also tried: speaker microphone distance, speaker features (age, gender, race; 61-dimensional) [Miao et al., 2016]

Comparison of Approaches

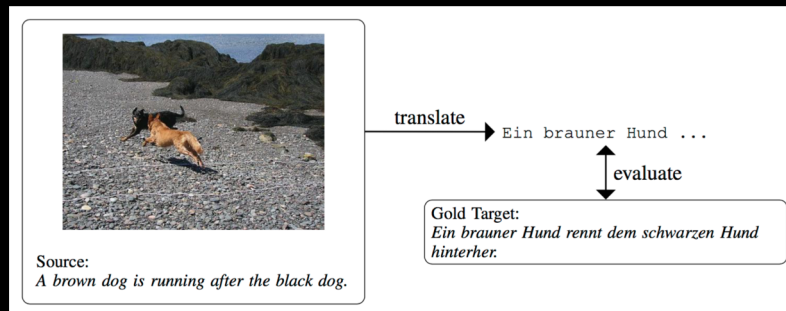
Model	Features	WER(%)	
DNN (Baseline)	----	23.4	
Adaptive Training	161-dim visual features	22.3	↓ 4.7%
Adaptive Training	100-dim speaker i-vectors	22.0	↓ 6.0%
Adaptive Training	261-dim fused features	21.5	↓ 8.1%

[Gupta et al., 2017]

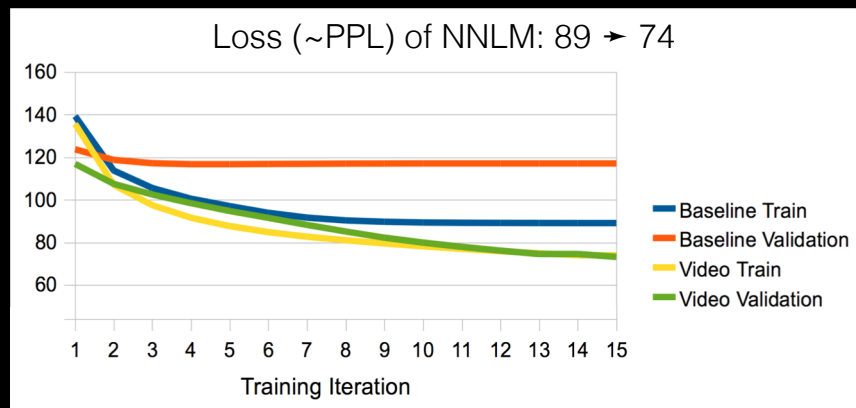
- AV adaptation does not beat i-Vector adaptation, but is in ballpark, somewhat complementary

Language Modeling

- Context aware language models easy with RNNs
 - [Zweig et al., 2012; ...]
 - Append context vector to word embeddings
- NMT of image captions [Specia et al., 2016]



Bi-LSTM LM (5-fold CV)



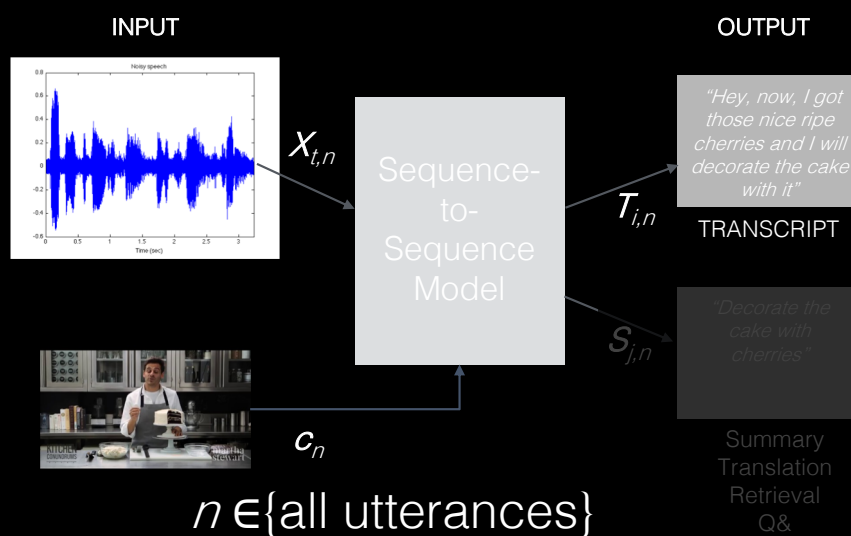
- 30-best lists from 23.4% WER DNN baseline
 - Re-score and re-rank with LSTM-LM
- 22.6% WER (15.6% Oracle WER)
 - Small but consistent improvements

Result Analysis – “indoor” vs “outdoor”

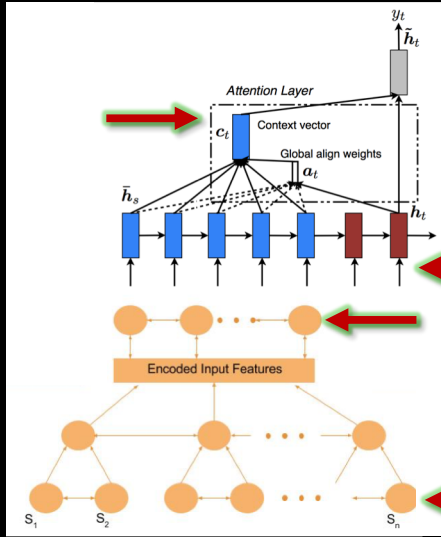
- Using object and place features only
 - AM+LM adapt.: 23.4% → 21.5% WER on 4h dev set (90h training)
- LM adaptation improves results across the board
 - 126/ 156 videos improve
- AM improves “noisy” videos
 - 55/ 156 videos improve (most are “outdoor”, according to their category)



Video as side-information in S2S ASR?



Adaptive Seq-2-Seq with Attention

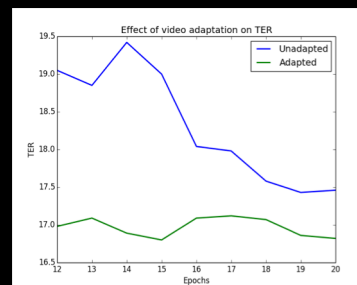
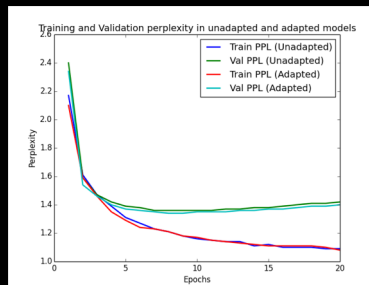


6+ ways of incorporating "visual context":

- Encoder feature shifts and appending features (AM)
 - Input layer, pyramid output
- At decoder (LM)
 - With attention mechanism
 - Co-Attention (2 sequences)
- At softmax layer (1G LM)

S2S Training Results (90h How-To)

- Appending 100d adaptation vector to 120d IMEL feature
- Best TER observed for later epochs, where perplexity increases
- Nice improvement in TER (17.5% → 16.8%)
- Also works for CTC models, but somewhat inconsistent



Audio-Visual ASR Results

- It is possible to adapt (condition) a E2E ASR Model to static context, like a domain
 - CTC and S2S models both work
- The error rates improve, integration with an adapted language model gives further gains
- **More experimentation is needed, but models seem to learn semantic properties of the (correlated) video**
 - Multi-task (CTC+S2S) training?
 - Determine best units: chars, BPE, **words**, ...
 - Shared representations have been learned?



Can you fly this thing?

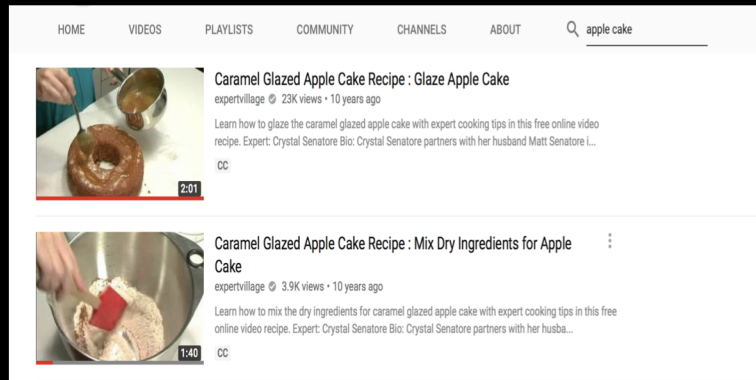


Not yet.
[...]
Let's go!



Multimedia Summarization

- Which how-to videos to watch, and why?



S2S Summarization



Results

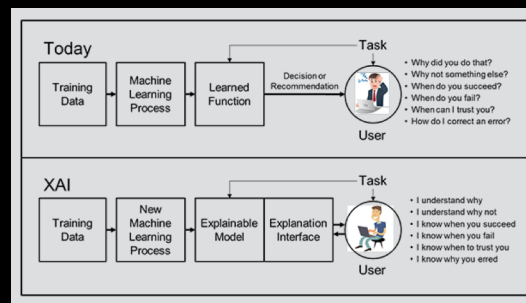
Model	Bleu-1	Bleu-2	Bleu-3	Bleu-4	Meteor, penalty=0	Rouge-L	Avg. words replaced
Baseline (original)	52.282	41.929	35.652	31.214	0.52	0.506	-
Without catch- phrases	33.811	22.731	16.699	12.862	0.36	0.370	6.70
Rule- based	22.152	10.059	5.527	3.345	0.21	0.164	-
Without catch- phrases	19.483	8.656	4.800	2.904	0.19	0.155	1.25

Ongoing Experiments

- Multi-Document Summarization
 - Take **triplets** of videos (anchor/ same/ different)
- Use a sequence-to-sequence model to generate **two** “descriptions” for **three** videos together
 - “similar” (portions of) videos or
 - “different” videos
- Experiment with different architectures ongoing
 - Triplet loss to encourage sharing and learning
 - Multi-modal features

Where To?

- Conversational Search: UIs without Screens
- Robotics – see what Humans see
- Explainable AI



Questions?

<https://www.clsp.jhu.edu/workshops/18-workshop>

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