Learning English with Peppa Pig

Anonymous TACL submission

Abstract

Recent computational models of the acquisition of spoken language via grounding in perception exploit associations between the spoken and visual modalities and learn to represent speech and visual data in a joint vector space. A major unresolved issue from the point of ecological validity is the training data, typically consisting of images or videos paired with spoken descriptions of what is depicted. Such a setup guarantees an unrealistically strong correlation between speech and the visual data. In the real world the coupling between the linguistic and the visual modality is loose, and often confounded by correlations with non-semantic aspects of the speech signal. Here we address this shortcoming by using a dataset based on the children's cartoon *Peppa Pig*. We train a simple bi-modal architecture on the portion of the data consisting of dialog between characters, and evaluate on segments containing descriptive narrations. Despite the weak and confounded signal in this training data our model succeeds at learning aspects of the visual semantics of spoken language.

1 Introduction

Attempts to model or simulate the acquisition of spoken language via grounding in the visual modality date to the beginning of this century (Roy and Pentland, 2002) but have gained momentum recently with the revival of neural networks (e.g. Synnaeve et al., 2014; Harwath and Glass, 2015; Harwath et al., 2016; Chrupała et al., 2017; Alishahi et al., 2017; Harwath et al., 2018; Merkx et al., 2019; Havard et al., 2019a; Rouditchenko et al., 2021; Khorrami and Räsänen, 2021; Peng and Harwath, 2022). Current approaches work well enough from an applied point of view, but most are not generalizable to real-life situations that humans or adaptive artificial agents experience. Commonly used training data consist of images or videos paired with spoken descriptions of the scene depicted: however, the type of input that a language learner receives from the environment is much more challenging. Firstly, speech is only loosely coupled with the visual modality in naturalistic settings (Matusevych et al., 2013; Beekhuizen et al., 2013). Speakers often mention concepts that are not present in the immediate perceptual context, or talk about events that are remote in space and/or time (for example past experiences or future plans).

Secondly, in addition to correlations between the visual scenes and the *meaning* of spoken utterances, there are also correlations with non-semantic aspects of the speech signal, such as the voices of specific speakers, as well as with non-speech ambient sounds. Although it is plausible that such non-semantic correlations can sometimes be useful to the learner in the general endeavor of making sense of the world, for the specific task of learning the semantics of linguistic units they are likely more often an obstacle, as they make it harder to zoom in on the meaning-bearing aspects of the audio signal.

In the current study we make a first step towards simulating the acquisition of language via grounding in perception in a more naturalistic scenario. Our main focus is on learning the meaning of linguistic expressions from spoken utterances grounded in video. We use the well-known children's cartoon *Peppa Pig* as a case study. Compared to commonly used video datasets, this dataset has a number of interesting characteristics. The visual modality is very schematic, the language is simple in terms of vocabulary size and syntactic complexity, and analysis of its linguistic features suggests its suitability for beginner learners of English (Kokla, 2021; Scheffler et al., 2021). Crucially, however, most of the speech in the videos

consists of naturalistic dialogs between the characters in which they do not only discuss the here and now, but also often use displaced language.[1] Thus, the utterances are only loosely and noisily correlated to the scenes and actions depicted in the videos.

This choice of data thus allows us to directly address the ecological limitations of the current approaches. In addition, the cartoon videos also contain comments interjected by the narrator. We use these for evaluating the acquisition of meaning as they are more descriptive and less noisy and allow us to measure performance, while controlling for speaker characteristics.

We implement a simple bi-modal architecture which learns spoken language embeddings from videos, and train it on the Peppa Pig dataset. Our contributions are the following:

- We evaluate model performance in terms of video fragment retrieval and additionally design controlled evaluation protocols inspired by the intermodal preferential looking paradigm (Hirsh-Pasek and Golinkoff, 1996);
- We carry out ablations of model components in order to understand the effects of pre-training for the audio and video encoders, the role of temporal information, and of segmentation strategies while training.

We show that despite the challenges of our naturalistic training data, our model succeeds at learning associations between the form of spoken utterances and their visual semantics. Moreover, even though the model rarely hears words in isolation, it captures aspects of the visual meaning of frequent nouns and verbs. Our ablation studies suggest that temporal information contributes to video modeling (especially for longer segments), and that self-supervised pre-training followed by fine-tuning of the audio encoder is key to the best performance.

2 Related Work

Early attempts at simulating grounded language learning focus on interactions between adults and young children while playing with a set of objects from different categories (Roy, 1999, 2002; Gorniak and Roy, 2003; Mukherjee and Roy, 2003). In a representative study from this series, Roy and Pentland (2002) use speech recorded from such interactions paired with different views of the visible objects to identify linguistic units (i.e. words) and visual categories, and to map these two modalities together. A hard-coded visual system extracts object representations from images, and spoken utterances are represented as phoneme probabilities generated by an RNN pre-trained on spectrograms. Their experiments on small-scale data (around 20 words and seven visual categories) show that the model can segment words and map them to visual categories.

2.1 Spoken Language Grounded in Images

The availability of datasets of images associated with spoken captions such as Flickr Audio Captions (Harwath and Glass, 2015), Places (Zhou et al., 2014) and Spoken COCO (Hsu et al., 2019) led to a rapid development of neural models of grounded language learning; see Chrupała (2022) for a comprehensive overview. In contrast to earlier approaches, these models are trained end-to-end directly on large datasets.

Following the architecture proposed in Karpathy et al. (2014) the visual and speech modality are usually encoded using separate pathways, and subsequently mapped into a joint representation space. Visual features are extracted from a pre-trained image classification model that processes the whole or a specific region of an image (however see Harwath et al. (2018), who train the model end-to-end on images and their spoken captions on the Places dataset). The audio encoder component in most models is either an adaptation of Harwath et al. (2016) which feeds a spectrogram of the speech signal to a convolutional architecture, or a hybrid architecture of convolutional followed by recurrent layers using Mel-Frequency Cepstral Coefficient (MFCC) features from the audio signal as input, as introduced by Chrupała et al. (2017).

The majority of models of speech grounded in images are optimized for and evaluated on image retrieval via spoken caption and vice versa. Additionally, a range of diagnostic analyses have been performed on the hidden representations of these models to study whether they encode the identity and boundaries of subword units such as phonemes and syllables (Alishahi et al., 2017; Harwath and Glass, 2019; Khorrami and Räsänen, 2021) as well as individual words (Chrupała et al., 2017; Havard

[1] For example, when Daddy Pig explains that they need to clean up before Mummy Pig sees the mess Peppa and George made, or when talking about plans to visit friends.

et al., 2019b). Moreover, in addition to examining form-meaning associations at the utterance level, Harwath and Glass (2017) explicitly learn a lexicon by extracting audio and image segments, clustering each modality separately, and mapping them together by calculating the pairwise similarities of their members in the joint semantic space.

2.2 Spoken Language Grounded in Video

There have also been recent attempts to learn spoken language grounded in video instead of static images. Boggust et al. (2019) sample audio-visual fragments from cooking videos; their grounded model treats video frames as still images ignoring the temporal dimension. Rouditchenko et al. (2021) integrate the temporal information when encoding videos from the Howto100m dataset (Miech et al., 2019), and perform better than previous work in language and video clip retrieval.

Models trained on instructional video datasets often do not generalize well to other domains. Monfort et al. (2021) highlight this limitation and show that training on their larger and more diverse Spoken Moments in Time dataset leads to better generalization. But the point remains that these video datasets contain descriptive speech, thus ensuring that there is a strong correlation between the spoken language and their visual context, a characteristic that is not representative of the experience of learning language in real world. We remedy this limitation by using a video dataset that does not guarantee a direct description of the visual context.

2.3 Child Language Learning from Video

There are many studies on young children learning language by watching videos; see Vanderplank (2010) for a survey. The main takeaway of these studies is that language learning is much more effective in a social, conversational setting than by passively watching videos (Kuhl et al., 2003; Anderson and Pempek, 2005; Robb et al., 2009), but learning does happen in such contexts. Importantly for our goal, techniques such as the intermodal preferential looking paradigm have been developed to systematically test young language learners' knowledge of words, syntactic structure and semantic roles (Hirsh-Pasek and Golinkoff, 1996; Bergelson and Swingley, 2012; Noble et al., 2011). Nikolaus and Fourtassi (2021) employ this evaluation strategy to test semantic knowledge at word and sentence level in their computational model of word learning from images. We adapt this approach to evaluate how our grounded model associates semantic information to spoken words and utterances from video.

2.4 Intra-linguistic Statistics

One further aspect of learning spoken language via visual grounding is the fact that grounding is only part of the story. Human children arguably infer substantial amounts of information about language structure and meaning from purely intra-linguistic co-occurrence statistics (e.g., Saffran et al., 1996). A similar mechanism is what allows written language models such as BERT (Devlin et al., 2019) or GPT-3 (Brown et al., 2020) to capture and exhibit relatively sophisticated linguistic knowledge. Loosely similar approaches have started to also make an impact for the spoken modality (e.g. Baevski et al., 2020; Hsu et al., 2021). Here we take a simple pre-training-based approach to integrating this type of self-supervision with learning-via-grounding.

3 Method

The main focus of this study is on the data and evaluation. We thus keep the components of our architecture simple, and follow established modeling practices whenever possible.

3.1 Dataset

We use the dataset provided by Papasarantopoulos and Cohen (2021) which consists of metadata for the set of 209 episodes (seasons 1–5) of the English-language version of *Peppa Pig*.[2] The annotations created by Papasarantopoulos and Cohen (2021) feature written transcriptions aligned with the audio as well as segmentation into *dialog* and *narration*.[3] Dialogs are the parts spoken by the characters, while narrations are comments inserted by the narrator, which are more descriptive in nature. All the narration segments are uttered by the same voice actor. We use the dialogs for training the model, and set aside the narrations for evaluation purposes only. A small portion of the dialog data is also used for validation. Specifically, out of the total 209 episodes, we use dialog from episodes 1–196 for training, and 197–209 for validation. We

[2]We purchased the corresponding Peppa Pig episodes on DVD support.

[3]The quality of the alignment and segmentation in this dataset is variable. In cases where exact alignment is needed, such as for word-level analyses, we re-align the transcriptions using `github.com/lowerquality/gentle`.

set aside narrations from episodes 1–104 for validation and 105–209 for testing. We disregard portions of the video which are annotated as neither dialog nor narration: this means our data consists mostly of video clips which contain some speech.[4] Table 1 shows the sizes of the training and validation splits. The vocabulary size of transcriptions corresponding to the training data is 5,580.

Split	Type	Size (h)	# Clips
train	dialog	10.01	15666
val	dialog	0.66	1026
val	narration	0.94	1467
test	narration	0.64	1006

Table 1: Duration in hours and number of clips (FIXED condition) for all dataset splits.

3.2 Preprocessing

Our model is trained to discriminate positive video-audio pairs from negative ones. The positive pairs are those that are temporally coincident in the original video file. In order to generate these training items we need to split the videos into fragments. When preparing training data, we use annotations to separate dialog and narration data, but we *do not* use alignment with transcriptions for further segmentation, in order to make the setting naturalistic. Processing long segments of video and audio is not tractable on commodity GPU hardware, and we thus segment the data into brief snippets roughly comparable in length to the duration of a short sentence or a phrase. We use the following two segmentation strategies:

Fixed Using this approach we simply split sections into fixed-length non-overlapping fragments of 2.3 second duration. This length is close to the mean duration of audio aligned to a single line of subtitles. The number of clips for each dataset split is shown in Table 1.

Jitter In this approach the mean duration of the segments is the same (2.3 seconds) but we randomly vary the length of the video, and independently, of the corresponding audio around this average duration. This means that (i) the segments can be partially overlapping and (ii) the video and the audio it is paired with are of different length. Specifically, we sample the fragment duration d (in seconds) from the following distribution:

$$d \sim \min(6, \max(0.05, \mathcal{N}(2.3, 0.5))) \quad (1)$$

The video is subsampled to 10 frames per second, and to 180×100 resolution.[5] The audio is converted to mono by averaging the two channels and the raw waveform is used as input. We use the original sample rate of 44.1 kHz (instead of downsampling to the 16 kHz sample rate used for pre-training WAV2VEC2) as we found out that this helps with generalization performance on the narration validation data.

For evaluation we have a number of different conditions and evaluation metrics described in detail in Section 3.4 and in some of these conditions we use the subtitles to guide segmentation.

3.3 Model Architecture

We adapt the general modeling framework from studies on spoken image-caption data (Harwath et al., 2016; Chrupała et al., 2017): our objective function is based on a triplet-like contrastive loss with margin which encourages the matching audio and video clips to be projected nearby in the embedding space, and mismatching audio and video clips to be far away:

$$\ell = \sum_{av} \left[\sum_{a'} \max(0, S_{a'v} - S_{av} + \alpha) + \sum_{v'} \max(0, S_{av'} - S_{av} + \alpha) \right] \quad (2)$$

where α is a margin, S_{av} is a similarity score between a matching audio-video clip pair, and $S_{a'v}$ and $S_{av'}$ denote similarity scores between mismatched pairs, i.e. negative examples from the current batch. Our heuristic to generate positive and negative examples is very simple: we consider an example positive if the audio is temporally aligned with a video clip in our data. Other pairs of audio-video clips are considered negative.

3.3.1 Audio Encoder

The audio encoder portion of the model consists of a SMALL WAV2VEC2 model (Baevski et al., 2020) pre-trained in a self-supervised fashion, *without*

[4] Manual analysis of a random sample of 50 segments split according to the method described in Section 3.2 showed that approximately 6% of them contained no discernible words.

[5] Performance is better with higher resolution, but it makes GPU memory requirements prohibitive.

any supervised fine-tuning.[6] The WAV2VEC2 architecture learns audio embeddings by self-supervised learning driven by a contrastive loss applied to quantized latent representations of masked frames, loosely inspired by the BERT approach to language modeling (Devlin et al., 2019).

The output of this module is a temporal sequence of 28-dimensional vectors. We pool this output across time using an attention mechanism with dimension-wise weights (Merkx et al., 2019):

$$\begin{aligned}\mathbf{A} =& \text{softmax}_t\left(\text{MLP}(\mathbf{X})\right)\\ \mathbf{z} =& \sum_t \left(\mathbf{A}_t \odot \mathbf{X}_t\right),\end{aligned} \tag{3}$$

where $\mathbf{X}$ is the tensor with the encoder output vectors for each time-step t: an MLP followed by a time-wise softmax is used to compute an attention weight for each time step and for each dimension. The pooling is followed by a linear projection to 512 dimensions and L_2 normalization. For our experiments we also use versions of the encoder where the `wav2vec2` weights are frozen, as well as a randomly initialized rather than pre-trained version.

3.3.2 Video Encoder

As a video encoder we use the 18-layer ResNet (2+1)D architecture (Tran et al., 2018), pretrained on the action recognition dataset Kinetics-400 (Kay et al., 2017). The pre-trained model is available via Pytorch.[7] This architecture implements 3D convolution by decomposing it into a 2D spatial convolution followed by 1D temporal convolution. The output of this module is aggregated using the attention mechanism with the same architecture as for the audio module, linearly projected to the same dimensionality as the audio (512) and L_2 normalized. For our experiments we also use a version of the video encoder without pre-training.

STATIC baseline As a baseline to investigate the contribution of temporal information to video modeling we swap the video ResNet (2+1)D with the 2D ResNet pre-trained on ImageNet, which embeds each video frame separately. These frame embeddings are then attention-pooled as with the standard video encoder.

[6] Available from `https://dl.fbaipublicfiles.com/fairseq/wav2vec/wav2vec_small.pt`.

[7] See `https://pytorch.org/vision/stable/models.html#resnet-2-1-d`.

To further investigate the impact of temporal information while controlling for model architecture, we evaluate model performance in a condition where we randomly scramble the video frames within a clip at test time, thereby removing any useful temporal information.

3.4 Evaluation

The most common approach to evaluation for visually grounded models trained on spoken image captions is caption-to-image retrieval (often combined with image-to-caption retrieval); this technique has been carried over from text-based image-caption modeling. With the standard spoken caption datasets this approach is unproblematic since the content of the captions is not correlated with extra-linguistic clues in the speech signal, such as speaker identity (since speakers are randomly assigned to captions) or non-speech environmental sounds. In such an artificial setting, a retrieval metric measures the ability of the model to match spoken utterances to images based on their semantic content. This is not the case for the *Peppa Pig* dataset: here we can expect that when a video segment depicts a particular character (e.g. George) then the audio in this segment is more likely to contain utterances spoken by the voice actor playing George. Moreover, some characters might have a tendency to talk about certain topics more often than others, and the model might pick up on these associations instead of paying attention to the actual meaning of the uttered words. Due to these factors, in a naive retrieval setting, a model could obtain a high score by mostly capturing these non-linguistic correlations.

In order to control for these factors we leverage the narrator speech in the videos. These utterances are always spoken by the same actor, so speaker identity cannot be used as a clue for matching video and audio. Furthermore, the narration segments are akin to video captions in that they tend to describe what is happening in the video and thus their semantic content is more strongly correlated with the content of the video than in the case of the dialog, which is also a desirable feature for the purposes of system evaluation.

3.4.1 Video Retrieval

For the retrieval evaluation, as for training, we also use both the FIXED and the JITTER segmentation strategies; however, for most conditions, we only report retrieval for the FIXED evaluation data.

We encode each audio clip in a candidate set sampled from the validation (or test) data using the speech encoder part of the model; similarly we encode each video clip using the video encoder. We then measure cosine similarity between the encodings of the audio clip and all the video clips. If the video clip corresponding to the audio is among the n most similar video clips, we count that as a success. The proportion of successes across all audio clips gives us the retrieval metric known as recall@n. In Section 5 we report recall@N of the complete model on narration test data for values of N between 1 and 10; for the rest of the experiments in this paper we focus on $n = 10$. We set the candidate set size to 100, and thus the random baseline for the recall@10 is 10%. In order to quantify uncertainty in this evaluation due to the test data we repeat this procedure 500 times with randomly sampled candidate sets and visualize the score distribution.

3.4.2 Triplets

The absolute value the recall@10 of this metric may be hard to interpret as it depends on the size and content of the candidate set. For this reason, we evaluate model performance using a simpler, controlled scenario, inspired by intermodal preferential looking paradigms in child language acquisition (Hirsh-Pasek and Golinkoff, 1996). The proposed metric can be seen as a multimodal version of the ABX score proposed in Schatz (2016).

We extract clips aligned to a single subtitle line, group them by length, and for each pair of same-length video clips,[8] we extract the audio from one of them (selected at random) – this is our *anchor*. The video clip from which the anchor was taken is the *positive* one, and the other video clip is the *negative* one. This triplet of stimuli forms a single test item.

We use the model's audio encoder to encode the anchor, and the video encoder to encode both video clips. We then check whether the anchor is more similar to the positive or to the negative clip in terms of cosine similarity (see Figure 1 for an example). More precisely, *triplet accuracy* is the mean over all triplets of the following quantity:

$$\frac{\text{signum}(\text{cosine}(A, P) - \text{cosine}(A, N)) + 1}{2} \quad (4)$$

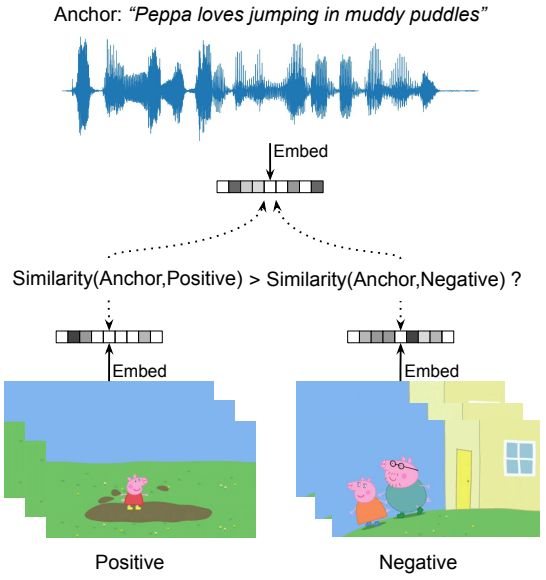

Figure 1: Triplets Evaluation: Given a reference audio sequence (anchor), we measure the model's performance at choosing the matching video (positive) over a random distractor video (negative).

where A is the anchor, P is the positive and N is the negative video clip. For this metric, we expect random-guessing performance to be at 0.5, and perfect performance to be at 1.0, regardless of the specific set of test items. We also quantify uncertainty by resampling the triplets 500 times from the dataset, and display the score distribution.

3.4.3 Minimal Pairs

While the triplet evaluation gives us a general idea about whether the model has learned a mapping between audio and video at the utterance level, it cannot tell us whether the model has acquired the grounded semantics of individual words.

To address this question, we probe the model's performance in a more targeted triplet setup, where the model is required to select the correct video from a pair of videos whose corresponding transcripts only differ in one target word. To construct the evaluation set, we search the transcripts of the validation data for phrases with minimal differences with respect to the most commonly occurring nouns, verbs and adjectives. We set the minimum frequency of the target word in our training set to 10, and the minimum phrase duration to 0.3 seconds.[9] Following Nikolaus and Fourtassi (2021), we pair every such triplet example with a corre-

[8] To keep test items independent, the pairing of video clips is done such that each clip only occurs as a member of a single triplet.

[9] For shorter sequences, we do not expect that the video contains enough semantic information to distinguish target and distractor. A phrase can also be a single word.

sponding counter-example to control the evaluation for linguistic biases in the dataset.

Figure 2 shows an example of how two counterbalanced test trials are constructed from audio and video clips. Here, the anchor A_{example} of the example triplet is the audio of *Peppa loves jumping*, the positive video P_{example} is the corresponding video, and the negative video N_{example} is the video corresponding to *George loves jumping*. In the counter-example triplet, the anchor $A_{\text{counterex}}$ is the audio of *George loves jumping*, and the positive and negative videos are flipped.

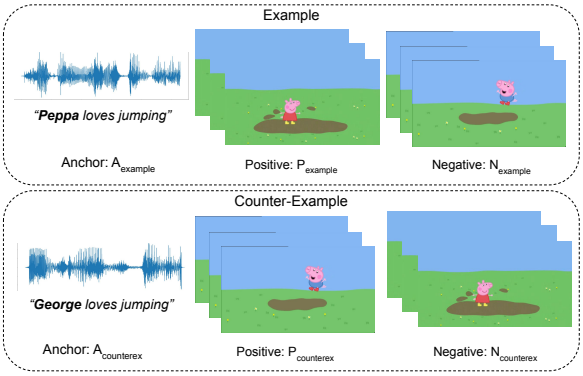

Figure 2: Example and counter-example triplets corresponding to minimal pairs *Peppa loves jumping* and *George loves jumping*.

We measure word accuracies by calculating the triplet accuracy for all triplets that contain a given word (e.g. *Peppa* in the previous example) either as target or distractor. That is, we take into account all cases where the model needs to use the meaning of the given word for either choosing or rejecting a video. We report word accuracy for all nouns and verbs for which we find at least 100 pairs of triplets in the validation set. We did not find enough examples for any adjectives, and thus did not include them in our evaluation.

4 Experimental Settings

We implement the architecture in PyTorch (Paszke et al., 2019). We use the Adam optimizer (Kingma and Ba, 2015) with the scheduling described in (Devlin et al., 2019). We train every configuration on a single GPU and stop training after 48 hours, with batch-size 8 and accumulating gradients over 8 batches, in 16 bit precision mode. For each model configuration we save model weights after each epoch and report results for the checkpoint which gets the best triplet accuracy on the narration validation data.

Our code is publicly available at `anonymized`, and can be consulted for further details of the experimental setup.

4.1 Sources of variability

We account for two sources of variance in the results. Firstly, for each model configuration we ran four separate training runs in order to account for the effect of random initialization. Secondly, we estimate the variance due to validation/test sample by resampling validation and test items 500 times. In the case of the minimal pairs evaluation, we employ bootstrapping with 100 re-samples. In most cases in Section 5, we pool variance from both sources and report overall spread, except when specifically focusing on the contribution of each source.

5 Results

Figure 3 shows recall@N for values of N between 1 and 10 for the complete model on test narration data in both FIXED and JITTER conditions. Both plots show that the value of recall@N increases monotnically. For the rest of this paper, we only report recall@10.

Table 2 presents the recall@10 and triplet accuracy scores on test narration data obtained with the complete model. In Section 5.1 we investigate the impact of various components of our training setup on performance as measured by recall@10 and triplet accuracy. In Section 5.2 we focus on the targeted evaluation via minimal pairs.

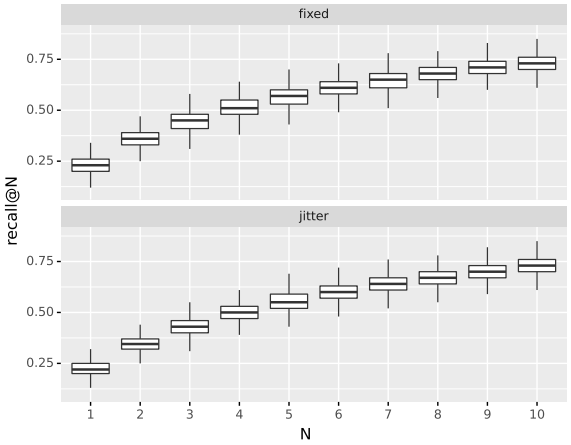

Figure 3: Recall@N as a function of N, for the narration test data. We show recall for the complete model, for the FIXED and JITTER retrieval evaluation settings.

R@10 (fixed)	R@10 (jitter)	Triplet Acc
0.73 ± 0.05	0.73 ± 0.04	0.91 ± 0.01

Table 2: Performance of the complete model on narration test data. We show the mean and standard deviation over the bootstrapped scores, pooled over four training runs (chance recall@10 = 10%; chance triplet accuracy = 50%).

5.1 Ablations

For completeness, we report results on both dialog and narration data. However, the scores on narration are our main focus as they are not confounded by speaker-based clues, and thus indicate to what extent the model learns aspects of utterance meaning.

For experiments in Section 5.1.1 we include each run as a separate boxplot to show the consistency of the results between runs in different training conditions. For the other experiments we collapse the results of the four runs to avoid clutter.

5.1.1 Pretraining and Fine-tuning

Results on different pretraining configurations are shown in Figure 4.

The best overall performance on both the dialog and the narration data is achieved with a model where both the video and audio encoder are pretrained before being fine-tuned on our data. On narration data, for both metrics, we see a clear ranking of configurations from best to worst: audio and video pretraining (AV), audio pretraining (A), video pretraining (V) and no training (None). Meanwhile for dialog data, the performance between A and V conditions is comparable. In the absence of any pretraining (None), some runs fail to converge, thus performing at chance level.

To further understand and disentangle the effects of audio pretraining and fine-tuning, we train a model with frozen parameters of the WAV2VEC2 module. The effect of this condition is shown in Figure 5. We find without fine-tuning of the WAV2VEC2 module, performance decreases substantially on both metrics. In other words, best performance is only achieved with pre-trained and fine-tuned models.

5.1.2 Jitter

Next, we evaluate a model that has been trained with varying video and audio lengths (JITTER). For fair comparison, here we report recall@10 for both FIXED and JITTER validation configurations. As seen in Figure 6, the effect of JITTER is only minor and that performance is comparable. However, we do observe some performance improvements when using JITTER in the minimal pairs evaluation (cf. Section 5.2).

5.1.3 Temporal Information

Finally, we explore the role of the temporal nature of the visual modality. Figure 7 compares the model with the regular video encoder with one using the STATIC baseline encoder. For this comparison we did not pretrain the video encoder in either condition, in order to remove the confound of the pretraining data.[10] Across all metrics, we observe substantial performance drops for the STATIC model, which has access to the same video frames, but does not have access to their temporal ordering. Additionally we investigate the effect of clip duration on this same comparison, using the triplet evaluation data. Figure 8 shows that the effect is nonlinear, and for the shortest clips temporal information does not help and may even have a detrimental effect.

Figure 9 shows the effect of scrambling the video frames along the temporal dimension at test time (note that here the video encoders are pretrained). As expected, we observe substantial performance drops when the model does not see the video frames in the correct order. For this ablation the differential impact of clip duration on the two conditions is very similar as in the STATIC ablation (figure not included).

5.2 Minimal Pairs

Table 3 presents results for the minimal pair evaluation along with several ablations. Models which are pretrained and fine-tuned with JITTER (row 0) perform best. In the first two configurations (rows 0 and 1), there is not much difference in the scores for verbs and nouns. However, we observe a substantial performance drop for both nouns and verbs if the WAV2VEC2 module is not fine-tuned.

If the model is trained without JITTER (row 2), performance drops substantially for nouns, but not for verbs. One possible explanation for this could be that the evaluation samples for nouns are on average shorter than those for verbs (nouns: $0.43s$ vs. verbs: $0.49s$), and a model trained with JITTER

[10] Note that there is one further confound we do not control for: the regular encoder has many more parameters than the STATIC one (31.5M vs. 11.7M).

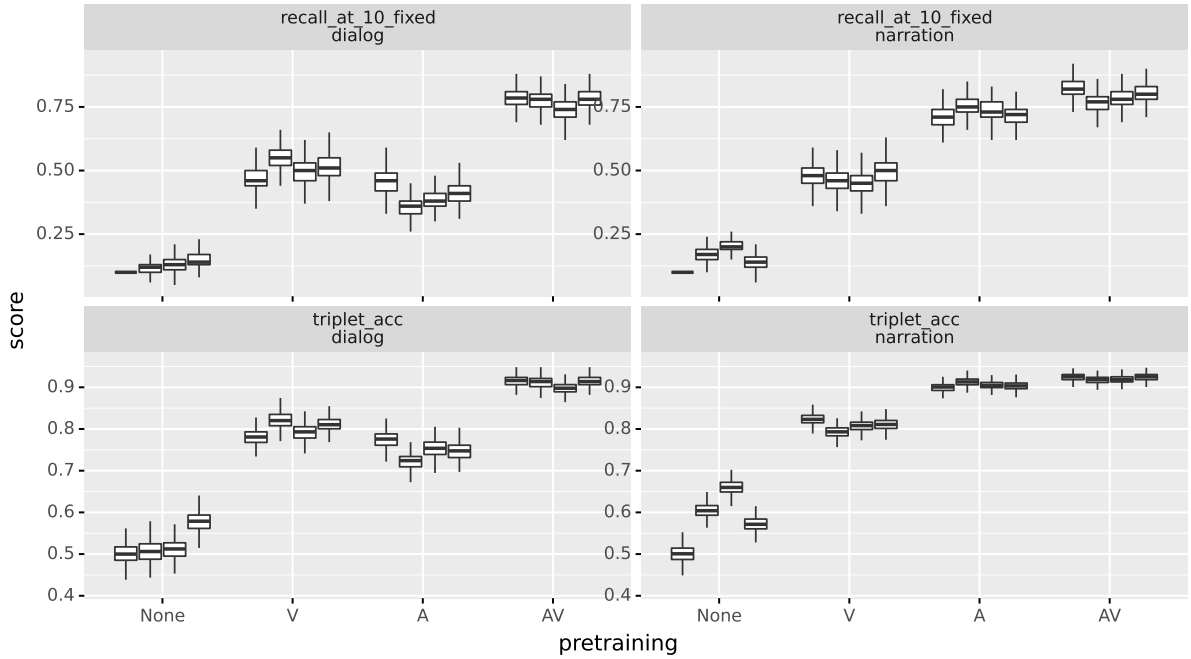

Figure 4: Effect of pretraining on performance on the dialog and narration validation data. The top row shows recall@10 (chance = 10%); the bottom row triplet accuracy (chance = 50%). Within each condition, we show scores for four separate runs. AV: pretrained audio and video; A: pretrained audio; V: pretrained video; None: no pretraining.

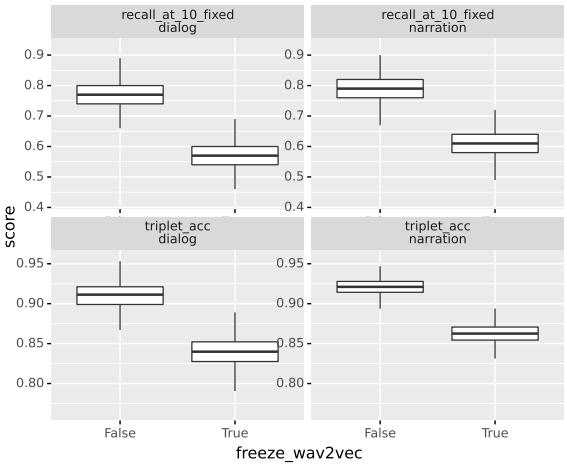

Figure 5: Effect of freezing the parameters of the WAV2VEC2 module on model performance, on the dialog and narration validation data (True: WAV2VEC2 frozen; False: WAV2VEC2 trained). The top row shows recall@10; the bottom row triplet accuracy.

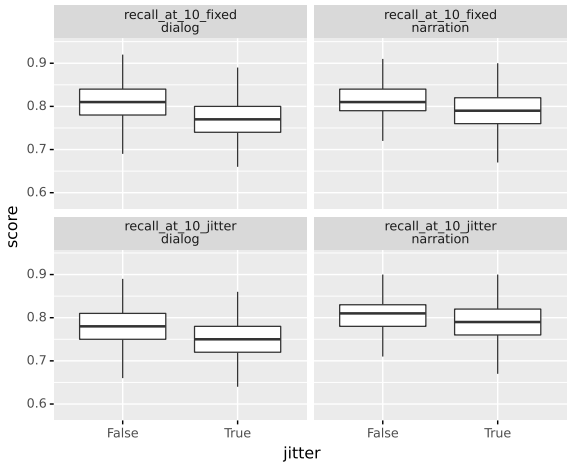

Figure 6: Effect of jitter on model performance, on the dialog and narration validation data (True: jitter; False: fixed). The top row shows recall@10 on FIXED evaluation data; the bottom row on JITTER-ed data.

performs better on short clips because it has been exposed to clips of varying duration during training. Supporting this hypothesis, we find a positive correlation between log duration of clips and accuracy, which is lower for models trained with JITTER (Pearson $r = 0.52$, $p < 0.001$) than for models without JITTER (Pearson $r = 0.69$, $p < 0.001$).

In line with the general results, we find that the benefit of audio pretraining (row 5) is greater than that of video pretraining (row 4). A model without any pretraining (row 3) only performs marginally above chance.

For a model trained with a STATIC video encoder (row 6), we compare performance to a model that was also trained without video pretraining (row

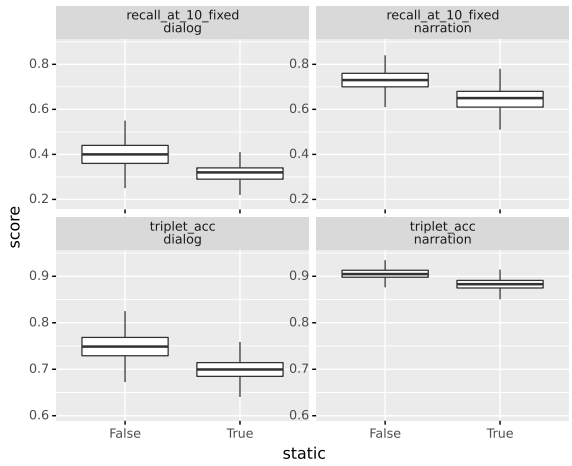

Figure 7: Effect of a STATIC image encoder on model performance, on the dialog and narration validation data (True: static video encoder; False: regular video encoder). The top row shows recall@10; the bottom row triplet accuracy. For both conditions only the audio modality is pretrained.

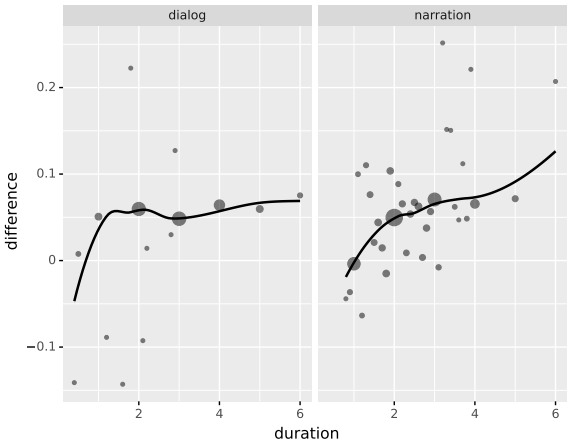

Figure 8: The effect of clip duration on the difference in performance between models with and without access to temporal information, on triplet data. Here we calculate the undiscretized triplet scores (i.e. $\text{cosine}(A, P) - \text{cosine}(A, N)$), average them over all triplets with the same duration, and for each duration compute the difference in the average between time-aware and static models. The size of the points corresponds to the number of triplets within each duration. The line of fit is a LOESS smoother weighted by size.

5) as done for the general results. We observe a slight performance improvement for nouns, and no significant difference for verbs. We suspect that temporal information is not crucial for the minimal pairs evaluation, because most evaluation samples are clips of short duration (on average: $0.44s$, i.e. 4-5 frames), thus limiting the benefit of the time dimension. As we saw in the analysis of clip duration (Figure 8), temporal information for such short clips does not improve performance, and could even have detrimental effects. In the alternative temporal ablation with scrambled video frames (row 7), we observe no significant performance drop compared to the base condition (row 0).

Figures 10 and 11 show per-word accuracy for nouns and verbs for the best performing model configuration. We observe substantial variance in the accuracy scores, suggesting that the difficulty to learn certain words varies. For example, the scores for *house*, *car*, and *cake* are the lowest. This could be because these concepts are not easy to ground, either because they are used in displaced speech or because they do not often refer to a similar visual entity. When looking at our evaluation samples, we find that indeed the word *house* is used in varying visual contexts (house entrance, whole house, inside the house, rabbit's house) and in displaced speech (talking about going to somebody's house). Cars are only sometimes completely visible, often we see only cartoon characters *in* a car. Regarding *cake*, it refers to either a whole cake, a slice, dough, or crumbs.

On the other end, performance for concrete words such as *ice*, *box*, and *sand* is the best, and indeed we find that in the evaluation examples these concepts are always present in the corresponding video and visually highly similar. Additionally, the words *Pedro*, and *Rebecca* are learned very well: They refer to *Pedro Pony* and *Rebecca Rabbit*, easily visually distinguishable from characters belonging to other species.

Further investigations with larger datasets are necessary to reveal the underlying reasons for difficulty, and relating them to predictors of age of acquisition in the child language acquisition literature (Roy et al., 2015; Frank et al., 2021).

6 Conclusion

We simulate grounded language learning in a naturalistic setting, where the connection between the linguistic and visual modalities is not always strong and is potentially confounded by correlations with non-semantic aspects of the speech signal. Our experimental results suggest that despite the challenges inherent to the naturalistic aspects of our training dataset, a simple bimodal architecture can capture aspects of visual meaning of individual words as well as full utterances, and generalize

ID	W2V Finet.	Jitter	V Pretr.	A Pretr.	Tmp Enc.	Tmp Frames	Nouns	Verbs
0	✓	✓	✓	✓	✓	✓	0.80±0.02	0.79±0.02
1		✓	✓	✓	✓	✓	0.72±0.01	0.71±0.01
2	✓		✓	✓	✓	✓	0.72±0.02	0.78±0.01
3	✓	✓			✓	✓	0.56±0.07	0.56±0.07
4	✓	✓	✓		✓	✓	0.69±0.02	0.69±0.01
5	✓	✓		✓	✓	✓	0.75±0.01	0.75±0.01
6	✓	✓		✓		✓	0.78±0.01	0.76±0.01
7	✓	✓	✓	✓	✓		0.79±0.02	0.78±0.02

Table 3: Minimal pair accuracies for nouns and verbs for different model ablations. W2V Finet: WAV2VEC2 module finetuned; A Pretr: Audio encoder pretrained; V Pretr: Video encoder pretrained; Tmp Enc: Video encoder with temporal information (not STATIC); Tmp Frames: Video frames in correct temporal order (not scrambled). Mean and standard deviation calculated over bootstrapped scores (100 re-samples), pooled over 4 training runs.

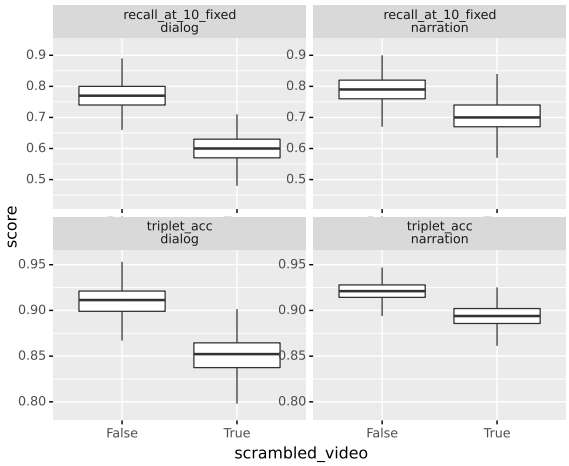

Figure 9: Effect of scrambling the video frames on model performance, on the dialog and narration validation data (True: video frames scrambled; False: video frames in order). The top row shows recall@10; the bottom row triplet accuracy.

well to narrative utterances featuring a single unseen speaker and a descriptive rather than conversational style. Our analyses show that generalization is substantially boosted by fine-tuning audio representations pretrained on unlabeled single-modality speech data. Fine-tuning a pretrained video encoder also makes a contribution, but is less crucial to generalization from dialog to narration. We also investigate the role of temporal information in learning form-meaning mappings and show that having access to time information facilitates learning, except for very short video segments.

6.1 Limitations and Future Work

To better understand what aspects of language are learning in our setting, we need to to carry out in-depth analyses of learned representations on subword, lexical, and phrasal levels. It would also be worthwhile to figure out the details of how specifically temporal information in video contributes to acquiring linguistic knowledge. Some analyses in this direction are currently constrained by the size of the evaluation dataset, and more large-scale datasets are needed in the future.

We model the acquisition of spoken language from language-internal correlations as well as from grounding in vision by fine-tuning an audio encoder pretrained on read speech. This approach is rather simplistic and does not match the real experience of language learners. It would be interesting to make the setting more realistic by using pretraining data which reflect a young learner's experience more closely, and to realistically interleave learning via self-supervision from speech and via grounding in vision. Ideally we would want to dispense with supervised pretraining of the video encoder as well and rather use a model pretrained in a self-supervised way also for this modality.

References

Afra Alishahi, Marie Barking, and Grzegorz Chrupała. 2017. Encoding of phonology in a recurrent neural model of grounded speech. In *Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017)*, pages 368–378, Vancouver, Canada. Association for Computational Linguistics.

Daniel R. Anderson and Tiffany A. Pempek. 2005. Television and very young children. *American Behavioral Scientist*, 48(5):505–522.

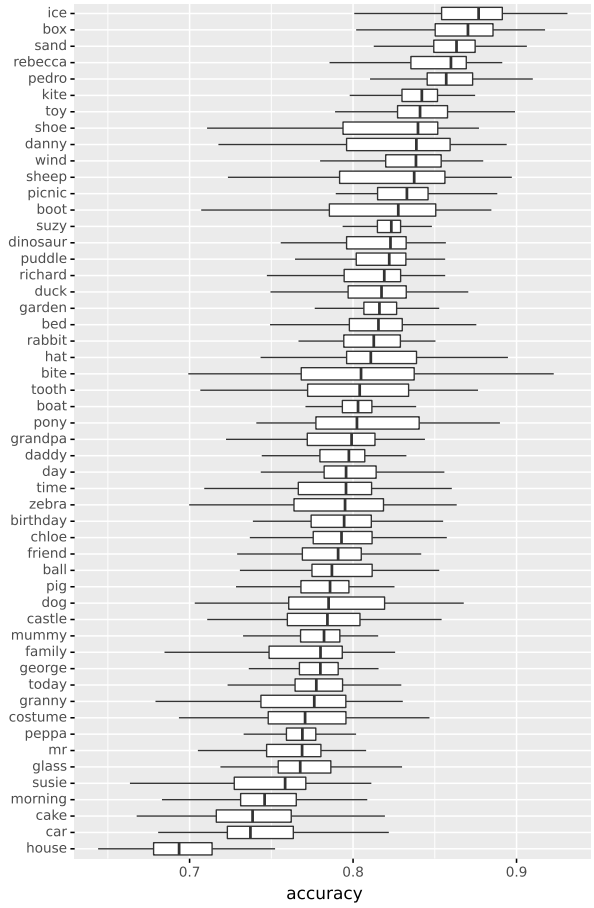

Figure 10: Per-word accuracies on the minimal pairs evaluation data for nouns.

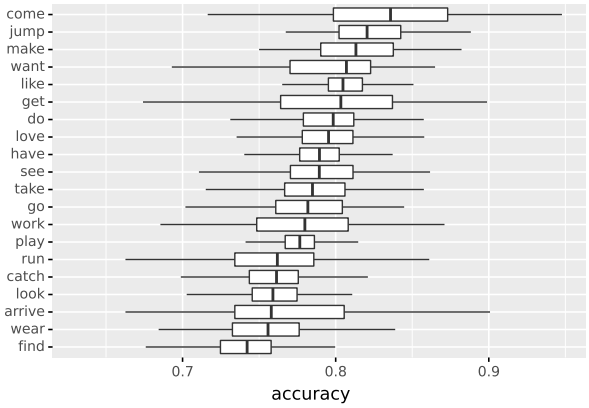

Figure 11: Per-word accuracies on the minimal pairs evaluation data for verbs.

2019. Grounding spoken words in unlabeled video. In *CVPR Workshops*, pages 29–32.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.

Grzegorz Chrupała. 2022. Visually grounded models of spoken language: A survey of datasets, architectures and evaluation techniques. *Journal of Artificial Intelligence Research*, 73:673–707.

Grzegorz Chrupała, Lieke Gelderloos, and Afra Alishahi. 2017. Representations of language in a model of visually grounded speech signal. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 613–622, Vancouver, Canada. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Michael C Frank, Mika Braginsky, Daniel Yurovsky, and Virginia A Marchman. 2021. *Vari-*

ability and consistency in early language learning: The Wordbank project. MIT Press.

Peter Gorniak and Deb Roy. 2003. A visually grounded natural language interface for reference to spatial scenes. In *Proceedings of the 5th international conference on Multimodal interfaces*, pages 219–226.

David Harwath and James Glass. 2015. Deep multimodal semantic embeddings for speech and images. In *2015 IEEE Workshop on Automatic Speech Recognition and Understanding (ASRU)*, pages 237–244. IEEE.

David Harwath and James Glass. 2017. Learning word-like units from joint audio-visual analysis. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 506–517, Vancouver, Canada. Association for Computational Linguistics.

David Harwath and James R. Glass. 2019. Towards visually grounded sub-word speech unit discovery. In *IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2019, Brighton, United Kingdom, May 12-17, 2019*, pages 3017–3021. IEEE.

David Harwath, Adria Recasens, Dídac Surís, Galen Chuang, Antonio Torralba, and James Glass. 2018. Jointly discovering visual objects and spoken words from raw sensory input. In *Proceedings of the European conference on computer vision (ECCV)*, pages 649–665.

David F. Harwath, Antonio Torralba, and James R. Glass. 2016. Unsupervised learning of spoken language with visual context. In *Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain*, pages 1858–1866.

William N. Havard, Jean-Pierre Chevrot, and Laurent Besacier. 2019a. Models of visually grounded speech signal pay attention to nouns: A bilingual experiment on English and Japanese. In *IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2019, Brighton, United Kingdom, May 12-17, 2019*, pages 8618–8622. IEEE.

William N. Havard, Jean-Pierre Chevrot, and Laurent Besacier. 2019b. Word recognition, competition, and activation in a model of visually grounded speech. In *Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL)*, pages 339–348, Hong Kong, China. Association for Computational Linguistics.

Kathy Hirsh-Pasek and Roberta Michnick Golinkoff. 1996. The intermodal preferential looking paradigm: A window onto emerging language comprehension. In D. McDaniel, C. McKee, and H. S. Cairns, editors, *Methods for assessing children's syntax*. The MIT Press.

Wei-Ning Hsu, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhotia, Ruslan Salakhutdinov, and Abdelrahman Mohamed. 2021. Hubert: Self-supervised speech representation learning by masked prediction of hidden units. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29:3451–3460.

Wei-Ning Hsu, David Harwath, and James Glass. 2019. Transfer Learning from Audio-Visual Grounding to Speech Recognition. In *Proc. Interspeech 2019*, pages 3242–3246.

Andrej Karpathy, Armand Joulin, and Fei-Fei Li. 2014. Deep fragment embeddings for bidirectional image sentence mapping. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pages 1889–1897.

Will Kay, João Carreira, Karen Simonyan, Brian Zhang, Chloe Hillier, Sudheendra Vijayanarasimhan, Fabio Viola, Tim Green, Trevor Back, Paul Natsev, Mustafa Suleyman, and Andrew Zisserman. 2017. The Kinetics human action video dataset. *CoRR*, abs/1705.06950.

Khazar Khorrami and Okko Räsänen. 2021. Can phones, syllables, and words emerge as side-products of cross-situational audiovisual learning? - A computational investigation. *Language Development Research*, 1:123–191.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*.

Natassa Kokla. 2021. Peppa Pig: An innovative way to promote formulaic language in preprimary EFL classrooms. *Research Papers in Language Teaching & Learning*, 11(1).

Patricia K Kuhl, Feng-Ming Tsao, and Huei-Mei Liu. 2003. Foreign-language experience in infancy: Effects of short-term exposure and social interaction on phonetic learning. *Proceedings of the National Academy of Sciences*, 100(15):9096–9101.

Yevgen Matusevych, Afra Alishahi, and Paul Vogt. 2013. Automatic generation of naturalistic child-adult interaction data. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, volume 35.

Danny Merkx, Stefan L. Frank, and Mirjam Ernestus. 2019. Language Learning Using Speech to Image Retrieval. In *Proc. Interspeech 2019*, pages 1841–1845.

Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. 2019. Howto100m: Learning a text-video embedding by watching hundred million narrated video clips. In *2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019*, pages 2630–2640. IEEE.

Mathew Monfort, SouYoung Jin, Alexander Liu, David Harwath, Rogerio Feris, James Glass, and Aude Oliva. 2021. Spoken moments: Learning joint audio-visual representations from video descriptions. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*.

Niloy Mukherjee and Deb Roy. 2003. A visual context-aware multimodal system for spoken language processing. In *Eighth European Conference on Speech Communication and Technology*.

Mitja Nikolaus and Abdellah Fourtassi. 2021. Evaluating the acquisition of semantic knowledge from cross-situational learning in artificial neural networks. In *Proceedings of the Workshop on Cognitive Modeling and Computational Linguistics*, pages 200–210, Online. Association for Computational Linguistics.

Claire H. Noble, Caroline F. Rowland, and Julian M. Pine. 2011. Comprehension of argument structure and semantic roles: Evidence from English-learning children and the forced-choice pointing paradigm. *Cognitive Science*, 35(5):963–982.

Nikos Papasarantopoulos and Shay B. Cohen. 2021. Narration generation for cartoon videos. Preprint: `https://arxiv.org/abs/2101.06803`.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc.

Puyuan Peng and David Harwath. 2022. Fast-slow transformer for visually grounding speech. In *Proceedings of the 2022 International Conference on Acoustics, Speech and Signal Processing*.

Michael B Robb, Rebekah A Richert, and Ellen A Wartella. 2009. Just a talking book? Word learning from watching baby videos. *British Journal of Developmental Psychology*, 27(1):27–45.

Andrew Rouditchenko, Angie Boggust, David Harwath, Brian Chen, Dhiraj Joshi, Samuel Thomas, Kartik Audhkhasi, Hilde Kuehne, Rameswar Panda, Rogerio Feris, Brian Kingsbury, Michael Picheny, Antonio Torralba, and James Glass. 2021. AVLnet: Learning Audio-Visual Language Representations from Instructional Videos. In *Proc. Interspeech 2021*, pages 1584–1588.

Brandon C Roy, Michael C Frank, Philip DeCamp, Matthew Miller, and Deb Roy. 2015. Predicting the birth of a spoken word. *Proceedings of the National Academy of Sciences*, 112(41):12663–12668.

Deb Roy. 1999. *Learning from sights and sounds: A computational model*. Ph.D. thesis, MIT Media Laboratory.

Deb K. Roy. 2002. Learning visually grounded words and syntax for a scene description task. *Computer speech & language*, 16(3-4):353–385.

Deb K. Roy and Alex P. Pentland. 2002. Learning words from sights and sounds: A computational model. *Cognitive Science*, 26(1):113–146.

Jenny R. Saffran, Richard N. Aslin, and Elissa L. Newport. 1996. Statistical learning by 8-month-old infants. *Science*, 274(5294):1926–1928.

Thomas Schatz. 2016. *ABX-discriminability measures and applications*. Ph.D. thesis, Université Paris 6 (UPMC).

Paweł Scheffler, Christian Jones, and Anna Domińska. 2021. The Peppa Pig television series as input in pre-primary EFL instruction: A corpus-based study. *International Journal of Applied Linguistics*, 31(1):3–17.

Gabriel Synnaeve, Maarten Versteegh, and Emmanuel Dupoux. 2014. Learning words from images and speech. In *NIPS Workshop on Learning Semantics*.

Du Tran, Heng Wang, Lorenzo Torresani, Jamie Ray, Yann LeCun, and Manohar Paluri. 2018. A closer look at spatiotemporal convolutions for action recognition. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 6450–6459.

Robert Vanderplank. 2010. Déjà vu? A decade of research on language laboratories, television and video in language learning. *Language teaching*, 43(1):1–37.

Bolei Zhou, Agata Lapedriza, Jianxiong Xiao, Antonio Torralba, and Aude Oliva. 2014. Learning deep features for scene recognition using Places database. In *Advances in Neural Information Processing Systems*, volume 27. Curran Associates, Inc.