Predicting a Song Title from Audio Embeddings on a Pretrained Image-captioning Network

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Abstract: Finding the name of a song from a piece played without the lyrics remains a long-standing challenge to music recognition services. In this work, we propose the use of a neural architecture that combines deep learned image features and sequence modeling to automate the task of predicting the song title from an audio time series. To feed our network with a visual representation, we transform the sound signal into a two-dimensional spectrogram. Our novelty lies in model training on the state-of-the-art Conceptual Captions dataset to generate image descriptions, jointly with inference on the Million Song and Free Music Archive test sets to produce song titles. We present extensive quantitative analysis of our experiments and show that using *k*-beam search our model achieved an out-domain BLEU score of 45.1 compared to in-domain performance of 61.3.

1 INTRODUCTION

Music Information Retrieval (MIR) is a growing field of research that recently underwent a profound mind shift from the use of handcrafted audio features toward representation learning to increase performance. Deep neural architectures have been proposed for a variety of MIR tasks, including speech denoising (Germain et al., 2018), mood detection (Delbouys et al., 2018), and the more widely explored topic, genre classification (Oramas et al., 2018). In this paper, we propose a deep learning approach to automate song naming, a task that generates a natural language short-phrase with an attempt to faithfully represents the content of an audio time sequence. In practice, automatic song title can benefit a diverse real-world application domains, including audio indexing, musical gaming, and personal memory assistant.

In the past decade, most prominent music descriptors used in MIR research were the Mel-frequency cepstral coefficients (MFCC) and chroma vectors (Urbano et al., 2014) that capture complementary timbral and tonal information from the underlying audio signal, respectively. The computation of the descriptors conforms to the same principle as they extract a time-frequency representation of the audio, filter out noise, map this representation to vectors, and accumulate them over time. This style of engineered features benefit effective machine learning, but is labor intensive and moreover is prone to extract discriminate data variability that is essential for building tailored predictors. In contrast, applying deep representation learning to automatic annotation and ranking of music audio (Hamel et al., 2011; Choi et al., 2017) and to polyphonic transcription (Boulanger-Lewandowski et al., 2012) had shown to considerably outperform models that use manual feature extraction.

Deep convolutional neural networks (CNN) have proved to greatly benefit many tasks in the domain of image understanding (He et al., 2016; Szegedy et al., 2016). This had subsequently motivated MIR researchers to express the input audio signal in a visual representation and learn musical features from a pretrained neural network on the large ImageNet dataset (Russakovsky et al., 2015). Recent musically inspired architectures have hence seen migrated to the use of a widely accepted audio format of a two-dimensional time-frequency spectrogram that is fed to a CNN (Pons et al., 2016; Oramas et al., 2018). Unlike an image that is an array of pixels interpreted spatially, the orthogonal dimensions of a spectrogram, time and frequency, makes the design of filters in the CNN top layer less intuitive. Respectively, audio filters learn proportional temporal dependencies on one axis, and timbral features on the other.

Recently, automatic description generation from images attracted broad attention from the natural language processing (NLP) and computer vision research communities. Among the diverse approaches, Vinyals et al. (2015) proposed an encoder-decoder ar-

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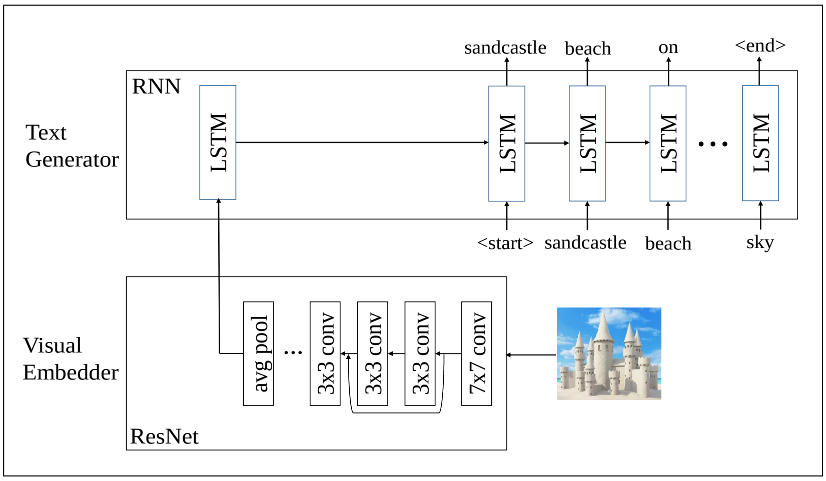


Figure 1: Neural model architecture: ResNet, a deep convolutional neural network is used to create a semantic representation of an image, which we then decode using an LSTM network. The vectorized image representation is fed into the network, followed by a special start-of-sentence token. The hidden state produced is then used by the LSTM to predict or generate the caption for the given image word-embeddings.

chitecture that uses a recurrent neural network (RNN) to generate captions conditioned on image features learned by a CNN. Alternately, Fang et al. (2015) explored a compositional neural model that detects words likely to be contained in a caption by applying CNN to image tiles, and then re-ranks a set of high-likelihood candidate sentences using learned linear weights. In their excellent surveys, Bernardi et al. (2016) and Hossain et al. (2019) offer an exhaustive critical review of model evolution, dataset choices and properties, and a discussion on evaluation metrics. Our neural model for generating song titles followed the Show-And-Tell (Vinyals et al., 2015) architecture, and leveraged the residual version of the Inception network (ResNet) (Szegedy et al., 2016) for the CNN module as shown in Figure 1.

We trained our model on the state-of-the-art Conceptual Captions dataset (Sharma et al., 2018) that has an order of magnitude more images than the most studied dataset to date, MS-COCO (Lin et al., 2014). Unlike the human curated MS-COCO, Conceptual Captions organizes samples as pairs of an image url and a description that were collected from a billion of English web pages and are thus by far more diversified. The initial image annotations are picked up from the alternative text attribute (alt) of a web page that is commonly supplied to an image. [1] However, alt-text sequences are free–form and tend to contain proper names that would make the training of song title generation a major challenge. In filtering the Conceptual Captions dataset, one of the more appealing processes to our task is the removal of noun modifiers and substituting named-entities with their hypernym.

In our baseline audio inference, we used a subset of the Million Song Dataset (MSD) (Bertin-Mahieux et al., 2011), a large-scale dataset that contains metadata and audio analysis for a million of contemporary tracks, which are legally available to Echo Nest (Jehan and Whitman, 2005). This exploratory subset is published on the UCI repository (Dua and Graff, 2017) and was originally targeted for the task of predicting the release year of a song from timbral features. In our work, we first associate a song title with its audio features, and then convert the timbral data to a tensor that we feed directly to the text generator, thus bypassing the ResNet stage all together.

In end-to-end evaluation of our neural model, we used the Free Music Archive (FMA) dataset (Defferrard et al., 2017). FMA provides full-length and high quality audio for over one hundred thousand tracks from thousands of artists. The song collections from this archive are distributed in variable counts of mp3-encoded audio data of either balanced or unbalanced genres. We used a group of 8,000 music tracks, each of a 30-second play time, gathered from eight top genres evenly with one thousand clips per genre. In our framework, we convert an mp3 song to a wave object from which we produce a spectrogram that is parameterized by the number of time frames and frequency bins. A consistent clip length for each track warrants a fixed-size input to the ResNet stage of our model.

The main contribution of our work is the learning of audio representations from a pretrained neural model that automatically generates descriptions from images, to predict musical titles. We hypothesize that image captioning and song naming are similar in con-

[1] https://en.wikipedia.org/wiki/Alt_attribute

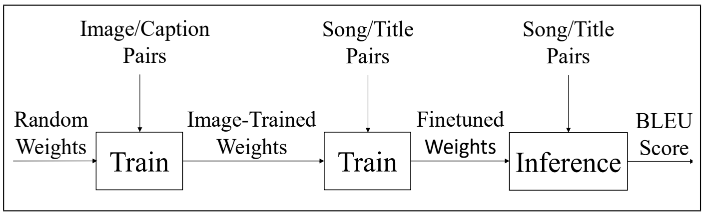


Figure 2: Our two-step training process for adapting the source visual domain to the target auditory cues.

text and thus make a constructive knowledge transfer plausible. To the extent of our knowledge, we are the first to propose a multi-domain collaboration of audio, natural language, and vision to solve a MIR task.

The rest of this paper is structured as follows. In Section 2, we introduce our baseline and end-to-end neural model architectures for predicting song titles. Proceeding to Section 3, we review the image captioning and audio datasets we used for training and inference, respectively. Section 4 provides initial data analyses, details our training methodology, and pursues domain similarity intuition. We then present extensive quantitative results of our experiments for various scenarios of representation learning, in Section 5. Discussion, summary, and identified avenues for prospective research are drawn in Section 6.

2 MODEL

Many proposed models that use deep neural networks (DNN) for image description generation (Vinyals et al., 2015; Fang et al., 2015; Ding and Soricut, 2017) were inspired by recent advances in neural machine translation (NMT). NMT architectures have shown state-of-the-art results in both the form of a powerful sequence model (Sutskever et al., 2014; Cho et al., 2014; Bahdanau et al., 2015), and more recently using the cross-attention ConvS2S (Elbayad et al., 2018) and the self-attention based Transformer network (Vaswani et al., 2017).

The task of image captioning uses a similar approach to NMT, but instead of encoding a variable-length text sequence to a fixed dimensional vector that is decoded to an output sentence, an image represented as a two-dimensional tensor (Paszke et al., 2017) is translated to its description. Moreover, rather than RNN, images are encoded using deep CNN. In our work, we used the most recent residual version 2 of the Inception architecture (He et al., 2016; Szegedy et al., 2016) to produce image embeddings, and follow Vinyals et al. (2015) with a Long Short-term Memory (LSTM) (Hochreiter and Schmidhuber, 1997; Chung et al., 2014) variant of recurrent networks to generate natural language descriptions.

In Figure 1, we review our neural model architecture for predicting song titles. Using a very deep ResNet, the model creates a semantic representation of either a natural image or an audio spectrogram that is then decoded in an LSTM network for generating variable-size text sequences. Our framework uses a two-step process depicted in Figure 2 to train our model and adapt the source visual domain to the target auditory cues by tuning network hyperparameters.

In training, we feed the model with images drawn from urls provided by the Conceptual Captions dataset (Sharma et al., 2018). The dataset retains images of which both dimensions are greater than 400 pixels that we randomly crop each into a consistent two-dimensional array of 256×256 pixels sampled from the raw image or its horizontal reflection. Each pixel renders a mean-subtracted 3-channel intensity.

We used deep visual representation that enjoyed great success in large-scale image and video recognition tasks (Simonyan and Zisserman, 2015). Pretrained on the large ImageNet dataset (Russakovsky et al., 2015), extremely deep residual networks (ResNets) prove significant accuracy gains from considerably increased network depth (He et al., 2016). Moreover, deep ResNets have an appreciable lower computational complexity compared to a much shallower VGGNet architecture (Simonyan and Zisserman, 2015).

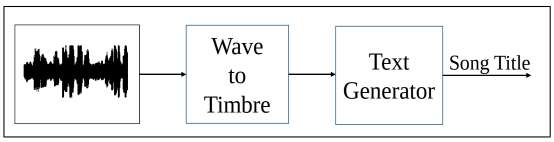


Figure 3: Baseline inference model: timbral engineered features are extracted from an audio signal and fed via a backdoor to the language generator.

Our model applies a residual network with a depth of 152 layers to encode an image into a 512×1 tensor. We strip off the last 1000-way fully-connected layer that produces probabilities through a softmax activation, and expose the global average-pooling stage of which we extract the image features. Following Ioffe and Szegedy (2015), we chose to invoke batch normalization in training our ResNet without requiring

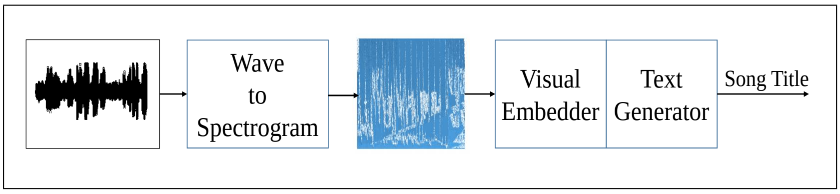


Figure 4: Mainline inference model: the audio signal is converted to a spectrogram that is fed to the visual embedder and follows the processing path of a natural image.

dropout to regulate the network. More formally, given a natural image denoted by I, the image embedding tensor, I_e, extracted by ResNet reduces to

$$I_e = \text{ResNet152}(I).$$

On the NLP side, we constructed a vocabulary V from the textual image descriptions provided by the Conceptual Captions train set. We used a dense d-dimensional representation of word embeddings (Pennington et al., 2014) that are stored in the matrix $E \in \mathbb{R}^{|V| \times d}$ and are looked up to feed the LSTM cells of the text generator. Special word embeddings were added to indicate the begin and end delimiters of a text sequence (Figure 1), and an unknown token that identifies out-of-vocabulary words. We use the colon notation $v_{i:j}$ to denote a sequence of vectors $(v_i, v_{i+1}, \ldots, v_j)$. Let $x_{0:T-1}$ be the word embeddings to enter the LSTM network, thus the output probability of the next word is defined by

$$p_{t+1} = LSTM(x_t). \;\; t \in \{0, \ldots, T-1\}.$$

The ResNet pipeline and the embedding matrix E map the image and words of its description text sequence to the same vector space, respectively. To avoid more easily overfitting to the image noisy content, we feed the image tensor I_e once as the first input of a dynamic length LSTM at time $t = -1$ (Figure 1).

In inference, we are given an audio signal and our goal is to predict a song title using a pretrained image caption network as the source domain. This is mainly motivated by the abundance of available image networks (Russakovsky et al., 2015; Simonyan and Zisserman, 2015) and on the other hand, the shortage of networks trained on audio data. We contrast title prediction quality of a baseline model that uses a hand-crafted feature set with a mainline model that lets the network learn the features.

In Figure 3, we show our baseline model. Timbral (MFCC like) engineered features are extracted from an audio signal, upscaled to match the dimensions of the ResNet output tensor (512×1), and then fed through a backdoor as input to the RNN text-sequence generator. Although proven highly effective in audio classification tasks at extremely reduced data rates, MFCC is a lossy representation and thus less optimal in a producer type environment we employ.

To synthesize high-quality sound for our generative network, a lossless representation of the audio signal is essential. In Figure 4, we show our mainline inference model that has the audio signal converted to a spectrogram, a time-frequency matrix representation $S \in \mathbb{R}^{F \times T}$, where F is the number of frequency bins and T the number of time frames. Spectrograms are commonly perceived as two-dimensional images with pixel intensities representing the strength of a frequency component at a given time frame (Wyse, 2017). Hence a spectrogram representation is favorably suggestive that vision-purposed networks, like ResNet, may apply directly to sound.

In a generative neural model, k-beam search is widely used to improve the output language quality. Our study compares inference performance and runtime of a greedy search ($k = 1$), which selects at each timestep the most likely word in the output sequence, with beam search of varying $k > 1$ that returns a list of the best k candidate sequences up to time t with length $t+1$ and discards the non-promising alternatives. We hypothesize that greedy search impacts performance adversely and analyze the runtime cost incurred with increased beam size. Both time and space complexities of beam search are linear with the number of the most promising k nodes to expand the graph per layer, and thus $O(kd)$, where d is the depth of the search.

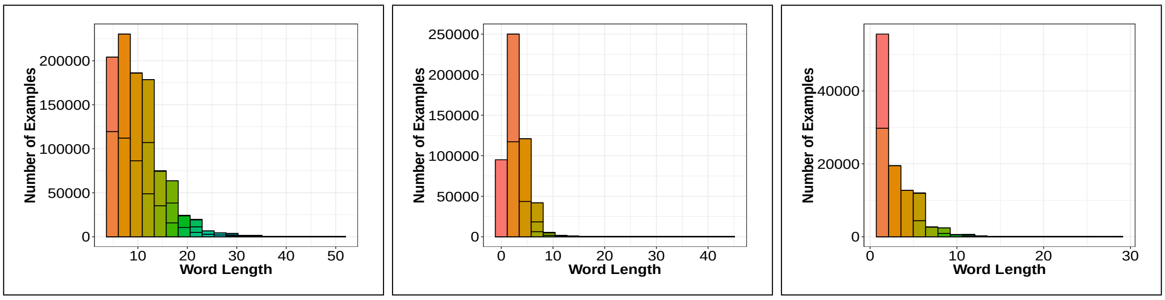
3 DATA

In this section, we summarize the datasets we used in our experiments to train and evaluate our neural model for predicting song titles.

3.1 Conceptual Captions

Our model is trained on the recently published Conceptual Captions dataset (Sharma et al., 2018). The dataset version released contains over three million image urls paired with natural language descriptions, [2] as the link between visual importance and descriptions inherently leads to the problem of text sum-

[2] https://github.com/google-research-datasets



(a) Conceptual Captions (b) Million Songs (c) Free Music Archive

Figure 5: Description distribution for (a) Conceptual Captions, (b) Million Song, and (c) Free Music Archive datasets.

Table 1: Statistics of description distribution across source and target datasets.

Dataset	Examples	Min Length	Max Length	Mean Length	StdDev Length
Conceptual Captions	1,000,000	4	50	10.31	4.67
Million Songs	515,576	1	135	3.09	1.86
Free Music Archive	106,573	1	28	2.98	2.11

marization in natural language processing. Conceptual Captions is by far the largest dataset introduced to date for the task of automatic visual description compared with one million captioned photographs in Im2Txt (Ordonez et al., 2011) and 328,000 images in the most broadly used MS-COCO (Lin et al., 2014). [3] Image annotations in Conceptual Captions were automatically distilled to avoid named-entities and result in a fairly concise vocabulary of slightly over fifty thousands unique tokens. This is prominent to effectively use the dataset as a source domain for transfer learning from large-scale vision data to a more constraint auditory space in generating waveform-originated song titles without proper names.

The Conceptual Captions dataset contains a total of 3,346,732 examples of which 3,318,333 are for training, 15,840 for validation, and 12,559 for test. We note that the test split is hidden and intended primarily for a challenge competition. In Figure 5a, we provide distribution of caption word length over a random sample of one million training examples. About 93.8 percent of the captions are of fifteen words or less and on average a caption is comprised of ten tokens, as evidenced in the statistics shown in Table 1.

3.2 Million Songs

To evaluate our baseline model (Figure 3), we used two complementary subsets of the Million Song dataset (Bertin-Mahieux et al., 2011), a collection of audio features and metadata for million western-style contemporary tracks. Originally intended for the task of estimating the release year of a song based on its audio features, the data of timbral features is publicly available on the UCI Machine Learning Repository (Dua and Graff, 2017), [4] and the correlated metadata set contains a list of all tracks that have the year information over a time span of almost ninety years, from 1922 till 2011. [5] To properly serve our purpose, we dropped the track release-year field from the feature set and appended to it a song title column that we extracted from the metadata set.

Our working dataset comprises 515,576 examples made of pairs of timbre features and song titles of which we randomly drew target samples for testing the baseline model (Figure 3). Manual-made MFCC-like features are represented each as a two-way vector of ninety elements. The first twelve coefficients of the feature vector are the canonical mean vector over all the audio segments, and the remaining 78 elements represent the covariance matrix.

In Figure 5b, we show word length distribution of song titles over the entire working set. Song title sequences of one to five words inclusive make up about ninety percent of over half a million tracks. The mean title length is of about three words, and while the maximum title size is of 135 tokens (Table 1), there is only one song of this word length and the immediately largest title to follow is of 45 tokens.

[3] https://github.com/cocodataset/cocoapi

[4] http://archive.ics.uci.edu/ml/datasets

[5] http://millionsongdataset.com/pages/tasks-demos/

Table 2: A sample of song titles from the Million Song and Free Music Archive datasets. All tokens are lowercased.

Million Songs	Free Music Archive
• trouble in mind • warm and sunny day • all i want is a spoonful • georgia man • the world does not revolve around you	• peel back the mountain sky • where is your love • queen of the wires • space power over-watch destroying evil rats • too happy

Table 3: Vocabulary token distribution in song titles for total tracks and 1000-track test sets across audio collections.

	Million Songs	Free Music Archive
Total	153,588	79,085
Test	966	1,573

3.3 Free Music Archive

We used the large-scale Free Music Archive (Defferrard et al., 2017), [6] to evaluate our end-to-end mainline model (Figure 4). The data contains both high-quality mp3-encoded audio and metadata for over one hundred thousand tracks, and is legally available for music analysis tasks. Most of the tracks have a sampling rate of 44,100Hz, a bit rate of 320Kbits/sec, and were produced in stereo. FMA offers a variety of downloadable collections based on size. In our work, we used an eight-balanced genre set of 8,000 tracks, each of thirty seconds play time. We built our target dataset for inference by randomly choosing mp3 file indices that we paired with the song title we extracted from the all-track metadata FMA provides.

The distribution of song title length across all 106,573 FMA tracks is illustrated in Figure 5c. Consistent with the title distribution in MSD, FMA song titles of five words or fewer take up about 89 percentage points of the tracks. Moreover, identical to MSD, average title length is about three words and is smaller than the mean caption word-length of ten. This length disparity between a song title and an image caption is at least suggestive to benefit transfer learning from vision to auditory domains. The maximum title length in FMA is of 28 tokens and thus spans the shortest description range of all the three datasets (Table 1).

4 SETUP

We measure song title quality by comparing the predicted title to a reference target, and chose to report unigram BLEU precision for our performance metric (Papineni et al., 2002). In the BLEU metric, higher scores indicate better performance.

4.1 Corpora

The datasets we used throughout our experiments underwent numerous cleanup steps. To tailor the Conceptual Captions source dataset to fit our task, we preprocessed the provided image urls and pruned ones that were either nonexistent or denied permission to user access. We found about ten percent of the raw training pairs to be unavailable. The caption vocabulary of the train set has 51,201 unique tokens and is sufficiently large compared to 996 and 1,573 distinct symbols for the target MSD and FMA song titles in their respective test sets of one thousand tracks each, as shown in Table 3. Using named-entity recognition with the Natural Language Toolkit (NLTK), we reviewed all song titles for the presence of any type of a named-entity. Given their short text sequence (Table 1), clips with named-entity titles were excluded from the test set. Similarly, tracks with titles that included words out of the English vocabulary were removed. In Table 2, we show lowercased samples of clean title text-sequences from MSD and FMA datasets.

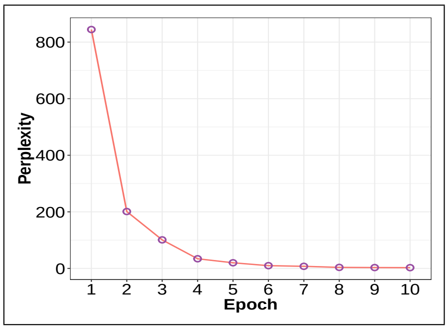
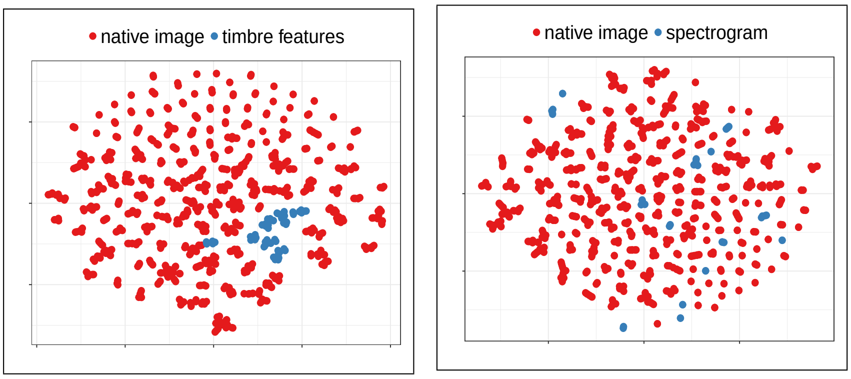


Figure 6: Epoch perplexity progression in in-domain training of our neural model.

Audios from the FMA dataset are in mp3 format and in the process of transforming them to spectrograms, we first created an R wave object (R Core Team, 2013). FMA tracks are consistently sampled

[6] https://github.com/mdeff/fma



(a) Timbre-Image similarity (b) Spectrogram-Image similarity

Figure 7: Audio-Visual similarity for (a) timbre-image and (b) spectrogram-image feature projection.

at 44,100Hz with 16-bit depth per sample, and as all clips are of a thirty-second play time, each thus spans roughly 1,323,000 samples. Sound waves have two-channel representation and stereo signals are converted to mono by either averaging both channels or selecting one of left or right, and then proceeding with the removal of DC offset by subtracting the mean. We used 1024 FFT points, a window size of 512, and an overlap of half the window points to generate a spectrogram from the finalized wave object. The spectrogram matrix of which we produce a sound image has 256 frequency bins and about 2,580 time frames. The number of time frames varies slightly across objects, as the play time is close to but not precisely 30 seconds for all tracks.

4.2 Training

In our work, we used domain adaptation to learn from descriptions bound to the visual content of a native image and predict song titles based on representations derived from auditory cues. We trained and validated our neural model (Figure 1) on the in-domain train and validation subsets of the Conceptual Captions dataset, and evaluated our baseline (Figure 3) and mainline (Figure 4) networks on out-domain test sets sampled from the MSD and FMA audio datasets, respectively. In-domain training parameters were fine-tuned after they were initialized to out-domain image-based weights.

We used PyTorch (Paszke et al., 2017) version 1.0 as our deep-learning research platform to train and evaluate our model for the task of description text generation. Embedding and hidden dimensions were set uniformly to 512, using a single-layer LSTM with a dropout of 0.2 to avoid train set overfitting. In training we minimized the cross-entropy loss and used the Adam optimizer (Kingma and Ba, 2014) with an initial learning rate of 0.001, as batch parameter updates were distributed across four CPU workers. Variable-length target descriptions are initially padded to the maximum sequence length in a train set, and then subsequently sequences are packed for efficiency. In Figure 6, we show the progression of perplexity in in-domain training across the first ten epochs, as the descent subsides at around the seventh epoch.

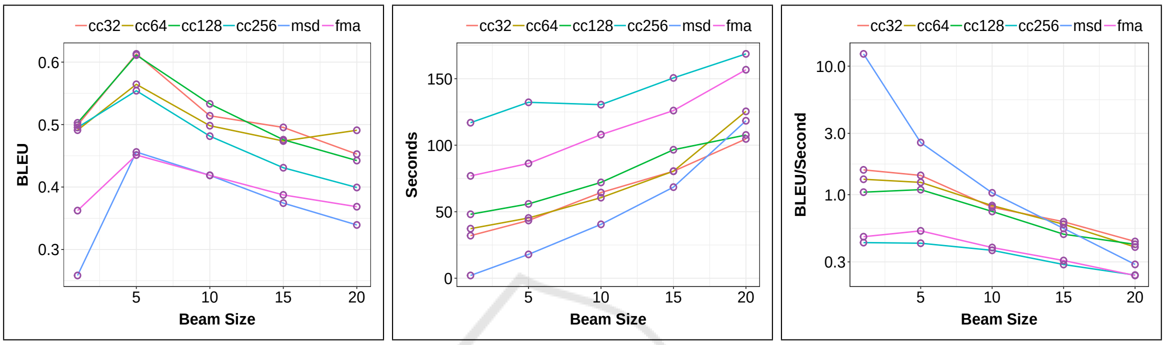
4.3 Domain Similarity

In this section, we analyze qualitatively the closeness between auditory and visual features, hypothesizing that similar source and target domains is one prerequisite to establish constructive transfer learning. We chose the embedding representation that feeds the text generator of our model in the form of a 512×1 tensor, as both sound spectrograms and native images conform to this interface format once they are processed by the ResNet pipeline. However, MSD features bypass the ResNet altogether (Figure 3) and thus involved the reshape of the ninety-dimensional raw timbre-vector to the 512×1 tensor shape, using random permutation of replicating indices.

We used t-distributed stochastic neighbor embedding (t-SNE) to project the large dimensional tensor space onto a two-dimensional extent (van der Maaten and Hinton, 2008) for visualization. We show proportional train and test set positional distributions of timbral and native image tensors in Figure 7a, and correspondingly spectrogram and native image tensors in Figure 7b. Upscaled timbral tensors appear fully contained in the visual cluster, while some sound image tensors are outliers or borderline at best and thus might be perceived as less optimal to knowledge transfer.

Table 4: BLEU performance scores in percentage points for in-domain and out-domain scenarios as a function of non-descending beam sizes ($k = 1$ implies greedy search).

Dataset	Tile Size	Tiles	1-beam	5-beam	10-beam	15-beam	20-beam
	32×32	64	49.9	**61.3**	51.4	49.6	45.3
Conceptual	64×64	16	49.1	56.4	49.8	47.4	49.1
Captions	128×128	4	50.3	61.1	53.3	47.6	44.2
	256×256	1	49.5	55.4	48.2	43.1	39.9
MSD	NA	NA	25.8	45.6	41.9	37.4	33.9
FMA	NA	NA	36.2	45.1	41.9	38.7	36.9



(a) BLEU Scores (b) Running Time (c) BLEU Rates

Figure 8: Model performance for in-domain and out-domain scenarios. Showing side-by-side (a) normalized BLEU scores, (b) running time cost, and (c) BLEU rates as a function of increased beam sizes.

5 RESULTS

We report quantitative quality of predicting song titles using hand-curated timbral features and spectrogram representations feeding our baseline (Figure 3) and mainline (Figure 4) neural models, respectively. Throughout our experiments, we contrast the sub-optimal greedy search that selects the highest scoring word at every stage of title generation with k-beam search that returns a list of the most likely candidate text sequences.

Depicted in percentage points, the rendered BLEU scores of our neural models are summarized in Table 4 for both in-domain and out-domain transfer scenarios. The scores are further parameterized by five discrete choices of beam sizes $\in \{1, 5, 10, 15, 20\}$, where $k = 1$ sets greedy prediction mode. In-domain scenarios use a subset of the Conceptual Captions validation set for inference and were evaluated for different number of image tiles arranged in a randomly selected crop size of 256×256 pixels from the larger raw image. Tiles are fed to the ResNet module individually and the final caption generation performance is the mean of all individual tile scores. Our best achieved in-domain score has 61.3 BLEU for an image configuration of 8×8 tiles, each an array of 32×32 pixels. Out-domain performance is only moderately lower than the top in-domain score by about 15.7 BLEU, as MSD timbral features has a slight edge over the sound image representation from FMA, with 45.6 and 45.1 BLEU, respectively.

Our results for varying beam search sizes in generating song titles are shown graphically in Figure 8. Consistently across all the transfer scenarios, prediction quality of song titles peaks for a beam size of five as presented in Figure 8a. Out-domain curves that are laid out distinctly at the bottom of the plot, initially climb precipitously from greedy search to a beam size of five, raising scores from about 0.25 to 0.45 BLEU, and then follow a fair descent as the beam size increases. In striking contrast to in-domain scores that sustain a more controlled upward slope. Then in Figure 8b, we review running time cost corresponding with each transfer scenario and beam size setting. As expected, running time cost increases linearly with a larger beam size. From a rather different perspective, BLEU-per-second derivative rates are shown on a logarithmic scale in Figure 8c. Out-domain MSD features render the sharpest decline in BLEU rates of roughly 4.9X as k increases from one to five, however this drop is rewarded with a marked performance boost of about 1.8X. In all, this quality-runtime tradeoff is deeply rooted in the beam search algorithm and confirms its complexity.

Table 5: Comparative model performance of text generation derived from audio signals, shown in BLEU scores.

Features	AudioCaps	Our Model	
	$k=1$	$k=1$	$k=5$
MFCC	34.1	25.8	45.6
Spectrogram	44.2	36.2	45.1

The task of generating natural language descriptions to music audio is unusually understudied in earlier research. Related to our work is the recent study by Kim et al. (2019) that creates text solely from audio input. They address the void of audio captioning by contributing the AudioCaps dataset that consists of 46K pairs of audio clips captured from YouTube video frames and newly collected human-annotated text descriptions. Kim et al. (2019) research evaluates numerous audio-captioning models for efficacy using both MFCC features and high-level spectrogram representations pretrained on VGGNet (Hershey et al., 2017). Unlike the captioning methods on the AudioCaps dataset that use 1-nearest search with audio features, our model emphasizes the tradeoffs of applying beam search to generated commentary. In Table 5, we show comparative performance as our model is slightly behind the AudioCaps captioning framework on greedy search, but present an advantage of 11.5 and 0.9 BLEU for MFCC and spectrogram representations, respectively, when using beam search of $k=5$. Although unable to evenhandedly contrast our model against, these results on their own appear to substantiate our transfer learning approach.

6 CONCLUSIONS

In this paper, we proposed to leverage learning of image embeddings that capture semantics for captioning to aid in predicting song titles from both timbral and spectrogram audio representations. We showed that by adapting visual descriptions to the auditory domain, our model performed in line with in-domain state-of-the-art vision data. Moreover, applying beam search over greedy predictions proved remarkable gains at a reasonable running time cost, however, extending the beam size to greater than ten drew a qualified diminishing return on performance. To the extent of our knowledge, the work we presented is the first attempt at a MIR task that translates sound cues to natural language sequences.

A key challenge to our work was the striking disparity between training and inference for conducting supervision steps to create descriptive input text to our model. The process of captioning a multimedia source is often governed by a visual bias attributed to a human judge, and hence captions tend to be extremely diverse, highly expressive, and correlate with either the image or audio clip they are paired with. In contrast, song titles are rather a loose summarization. They may be based on either the lyrics or the tune, and in many cases the song title is given before the music has been composed, or even edited later by the performing artist.

We envision several directions as a natural progression to improve our work. The use of additive attention in the recurrent text generator only marginally improved performance for image captioning systems, however, replacing the LSTM network of our model with the self-attention transformer architecture is worthy of pursuing and potentially gaining efficiency. Using the most deepest pretrained ResNet available have incurred the cost of increased inference time and memory footprint, thus exploring a shallower network is a reasonable step to benefit our model runtime with no apparent performance loss. Although the music category was discarded and set for future AudioCaps exploration, training our model on the AudioCaps dataset is likely to boost semantic similarity between source and target domains and thus benefit the quality of song title generation. Lastly, constructing a music dataset that associates the song title with the lyrics for each audio clip adds an essential dimension in evaluating our task.

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