match between the distributions of training and test data acquired under different recording conditions. FPDA is based on the projection of both source and target domain features onto a common subspace using a subset of the eigenvectors of the sample covariance matrix of the source domain data. After standardizing the spectrograms extracted from the source domain in a band-wise fashion, the sample covariance matrix $\mathbf{V}_{\mathrm{s}}$ of the source domain data matrix and the respective eigenvectors and eigenvalues are calculated. The eigenvectors corresponding to the L largest eigenvalues are retained as matrix $\mathbf{V}_{\mathrm{s}}^{(L)}$ and using this matrix source domain and target domain data are projected onto a common subspace as $\mathbf{X}_{\mathrm{S}} = \bar{\mathbf{S}}_{\mathrm{2D}}\mathbf{V}_{\mathrm{s}}^{(L)}$ and $\mathbf{X}_{\mathrm{T}} = \bar{\mathbf{T}}_{\mathrm{2D}}\mathbf{V}_{\mathrm{s}}^{(L)}$.

There are several differences between the application of FPDA in Acoustic Scene Classification (ASC) [15] and our application scenario for real-time piano transcription. Firstly, in [15], source and target domain data contain the same audio signal recorded simultaneously on different recording devices with a constant length of ten seconds, whereas the files contained in our source domain data have entirely different musical content as compared to the target domain data. Moreover, the number of samples varies greatly throughout both the source and target domain dataset in our case. For this reason and for FPDA to be applicable w.r.t. a real-time piano transcription scenario, we chose $L = 16$, so that the DA can be applied in a block-wise fashion, 16 frames at a time. To use the domain-adapted features as input for the piano transcription model, we project the features back to the original feature space as $\hat{\mathbf{S}}_{\mathrm{2D}} = \mathbf{X}_{\mathbf{S}}\mathbf{V}_{\mathrm{s}}^{(L)^T}$ as $\hat{\mathbf{T}}_{\mathrm{2D}} = \mathbf{X}_{\mathbf{T}}\mathbf{V}_{s}^{(L)^T}$. Then, the MPE model is trained on the resulting modified source domain data.

3. MULTI-PITCH ESTIMATION

3.1 Recent Approaches

While traditional MPE methods mostly relied on spectral decomposition techniques such as non-negative matrix factorization (NMF) [16], modern methods are based on different neural network (NN) architectures [17]. Hawthorne et al. [18] propose a general purposed piano transcription model that combines two branches of convolutional recurrent neural networks (CRNNs), which jointly predict the pitches and onset times of played piano notes. Kong et al. [19] proposed a high-resolution AMT system consisting of several CRNNs acoustic models dedicated to different tasks such as velocity, onset and offset regression. More recently, generic encoder-decoder architectures such as transformer networks have been used to remove the need of custom NN design, as done by Hawthorne et al. [20].

3.2 Model Architecture

Following recent advances in the field of computer vision, the U-net architecture is employed for different MIR tasks. In particular, it was used for different AMT tasks such as bass transcription [21], melody transcription [22, 23], as well as polyphonic piano transcription [24]. The structure of a U-net resembles an autoencoder, but is extended by skip connections between encoder and decoder blocks. Input features are first processed by an encoder that sequentially reduces the time-frequency resolution. The intermediate features are then handed over to the decoder part at the so-called bottleneck, where the compression is strongest. In the decoder, the time-frequency resolution is gradually restored by upsampling and interpolation. The main goal is to train the U-net such that it learns a mapping function from a spectrogram-like audio representation to a piano roll representation. In this study, we consider MPE as binary classification task, where each pitch can be either active or inactive at a given time frame. The encoder of our U-net model comprises three layers with alternating blocks of convolutional filter blocks and max pooling. In the decoder, bilinear interpolation operations are used for upsampling. Intermediate activations at similar levels in the encoder and decoder are connected by skip connections. The model output lies in the same feature space as the input features, but with a reduced frequency resolution of 72 bins instead of 216 bins.

The model was trained for 300 epochs with the Adam optimizer at an initial learning rate of $5 \cdot 10^{-4}$, early stopping patience of 20, and the binary crossentropy loss function.

3.3 Audio Representation

The MPE model expects input features as an harmonic Constant-Q transform (HCQT) [25] $H_{h,f,t}$ indexed by harmonic ratio h, frequency f, and time t. For any harmonic $h > 0$, we compute a standard Constant-Q transform (CQT), where the minimum frequency is scaled by the harmonic ratio h. For this MPE task, the HCQTs are computed for the harmonic ratios $h \in \{0.5, 1, 2, 3, 4, 5\}$, that is, one sub-harmonic below the fundamental frequency ($h = 0.5$), the fundamental frequency ($h = 1$) and four harmonics above ($h = [2, 3, 4, 5]$). As the fundamental frequency and the first harmonic often contain similar harmonic patterns [25], one sub-harmonic below the fundamental is included to distinguish between the two.

Features are extracted with the *librosa* Python library [26] with a hopsize of 512 samples, a sampling rate $f_{\mathrm{s}} = 22.05\,\mathrm{kHz}$, a frequency resolution of 36 bins per octave (bpo), and a minimum frequency for the CQT of $f_{\mathrm{min}} = 32.7\,\mathrm{Hz}$. This results in input features of dimension $\mathbf{X} \in \mathbb{R}^{M \times K \times C}$, with the number of time frames $M = 16$ for patch-wise processing, number of frequency bins $K = 216$, and amount of channels $C = 6$.

4. DATASET

4.1 Source Dataset

The U-net MPE model was trained and tested on subsets of the MIDI Aligned Piano Sounds (MAPS) dataset [1]. We used the dataset split labelled "Configuration 2" by Sigtia et al. [27], which divides MAPS into 210 synthesized

audio files for training and 60 real-world audio recordings for test data. The audio and aligned MIDI data used for training were generated using synthesis software based on high-quality sample libraries, whereas the test set contains piano recordings from a MIDI-controlled Disklavier which was recorded on two omnidirectional Schoeps microphones in a studio setting. We refer to the training data as `MAPS-train` and test data as `MAPS-test`.

4.2 Target Dataset

To assess the selected DA methods, we require a dataset of multiple transcribed piano recordings which cover different mobile devices as recording devices, recording locations with different acoustical properties, and various acoustic piano models (upright and grand piano). Because no openly available dataset fulfilled all our requirements, we created a new dataset called `IDMT-PIANO-MM` [28].

`IDMT-PIANO-MM` contains a total of 432 audio files, with a total duration of four hours and seven minutes, and 72 MIDI files corresponding to 72 unique piano performances recorded simultaneously on five recording devices (3 smartphones, 2 tablets) and a high quality stereomicrophone. The 72 MIDI files were generated and aligned manually to match the actual piano performance. The recording environments range from small rooms to large lecture halls. Three grand pianos, four upright pianos, and one electronic stage piano of various age, brand and price segments were recorded. In each room we recorded a human piano performance of a self-composed swing pattern, chord progression, a chromatic scale, as well as sections (between 24 s and 54 s) out of five classical music pieces and one ragtime piece.

5. ANALYZING DOMAIN SHIFT

5.1 Investigation of Microphone Mismatch

As the first step to quantify microphone mismatch, we compute the spectrum correction coefficients as described in [29] to compare the acoustic characteristics of different recording devices. To start, we choose a reference device r, which corresponds to a high-quality recording microphone, and compute the correction coefficients of all mobile devices d with respect to the reference. By comparing the frequency responses of the device and the reference for each frequency bin, we obtain a vector of multiplicative correction coefficients, which allows to make the frequency response of the device d resemble the one of the reference device r. Figure 2 illustrates the band-wise coefficients obtained for each mobile device. The correction coefficients show that there are considerable differences among the recordings associated to the different devices and their microphones. This confirms the microphone mismatch condition and suggests there is a domain shift between the training data from MAPS and the test data recorded with different mobile devices.

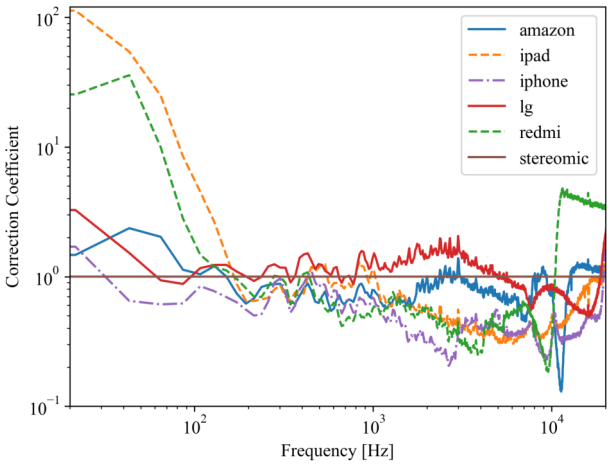

Figure 2. Frequency-dependence of the spectrum correction coefficients for all devices in respect to the `stereomic` microphone.

5.2 Quantifying Domain Shift

Due to the observed differences in the acoustic characteristics of the recording devices, we expect a measurable domain shift, which we quantify using the representation shift metric proposed by Stacke et al. [30]. The main idea is to compute an abstract representation of source and target domain features from a latent representation within a deep neural network and compare the data distributions between both domains in this latent feature space. In our experiments, we computed the activations after the last convolutional layer of the encoder in the U-net MPE model to measure domain shift, as we expect the highest degree of abstraction here.

In [30], the layer activations at layer l and filter f are averaged across the two spatial dimensions of a feature map. Since we deal with audio instead of images, these dimensions correspond to time frames and frequency bins. As the convolutional neural network (CNN) structure used in [30] is not directly comparable with the U-net architecture, we assumed that the U-net only has one filter operation per layer for simplicity. The mean value of a layer activation $\phi_l(x)$ at layer l is denoted as

$$c_l(x) = \frac{1}{N}\frac{1}{K}\sum_{i=1}^{N}\sum_{j=1}^{K}\phi_l(x)_{i,j} \tag{1}$$

with the number of time frames N, number of frequency bands K, and i and j as time and frequency index of the feature map, respectively. The mean values of layer activations are aggregated over all input features of a domain. The probability density function (PDF) of all mean values is approximated by computing a probability density histogram with 500 bins for each HCQT channel. The resulting PDFs are averaged over all HCQT channels. Finally, we compute the representation shift r as the mean distance between the distributions of the source and target domain. We employ the Wasserstein distance, which is a symmetric distance measure that can be seen as the least amount of

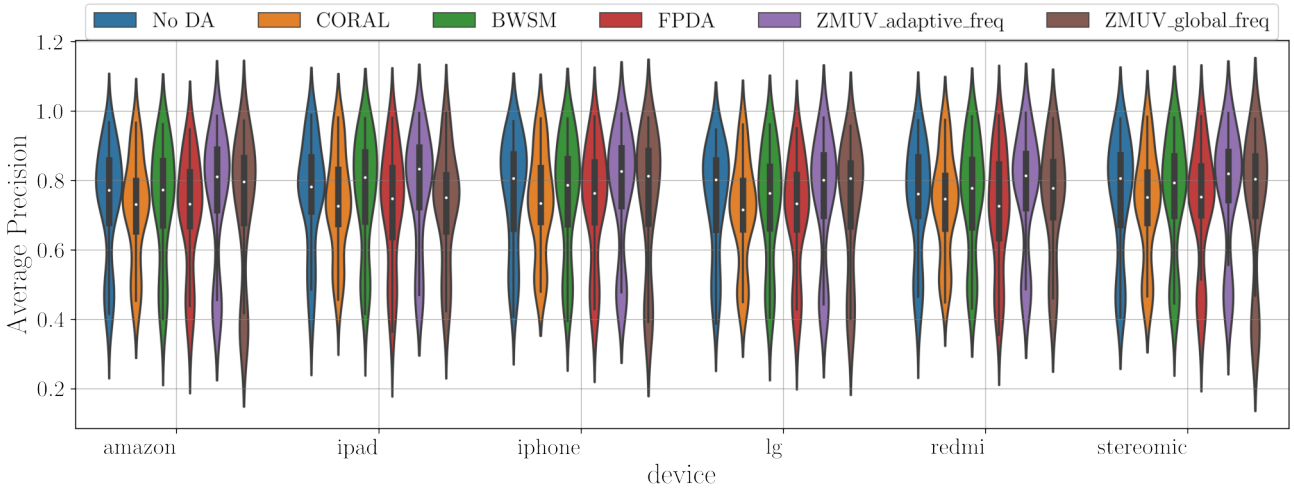

Figure 3. Performance of the MPE model on `IDMT-PIANO-MM`. The average precision score is presented for different DA methods grouped by recording devices.

Domain Pairs	r
`MAPS-train` vs. `IDMT-PIANO-MM`	0.035
`MAPS-train` vs. `IDMT-PIANO-MM-BWSM`	0.029
`MAPS-train` vs. `MAPS-test`	0.029

Table 2. Representation shift r based on the Wasserstein distance between source training data and source test data (`MAPS-train` vs. `MAPS-test`), source training data and target data (`MAPS-train` vs. `IDMT-PIANO-MM`), source training data and with BWSM domain-adapted target data (`MAPS-train` vs. `IDMT-PIANO-MM-BWSM`).

effort required to align two distributions w.r.t. the amount of data and the distance that has to be moved [30]. The representation shift between the used datasets is given in Table 2. The DA method BWSM was chosen as, in contrast to other DA methods, source domain data is not modified, which enables to directly compare the implementation with and without DA with identical MPE models.

6. IMPACT OF DOMAIN SHIFT ON PERFORMANCE

The performance of the MPE model is tested by comparing the estimated pitches with MIDI data as ground truth per frame. We chose mean Average Precision (mAP), i. e., the area under the precision-recall curve [31], as an evaluation metric, which is denoted as Average Precision (AP) in the following. Unlike other popular ML evaluation metrics like F-score or accuracy, AP does not depend on a particular binarization threshold for the pitch activity predictions.

6.1 Effect of Domain Adaptation

Figure 3 shows the AP scores of the U-net MPE model on the benchmark dataset separated by recording device. It shows that the microphone mismatch has no significant effect on the performance of the MPE model. Presumably as a direct consequence, we observe only little variation in transcription performance caused by DA. `ZMUV adaptive` performs consistently best, `ZMUV global` and `BWSM` report a similar performance as using no DA, and with `FPDA` and `CORAL` the AP scores are lowest amongst all DA methods, including not applying any DA.

6.2 Impact of Musical Content and Acoustic Context

We also assessed the impact of other parameters on the MPE performance, such as room acoustics and musical pieces. Our results showed no significant influence of the room and instrument characteristics towards the MPE performance. In contrast, the musical content shows the greatest impact on transcription performance. Figure 4 displays the influence of music content on the AP score when no DA or different DA methods are applied. Due to missing annotations of offsets, we assume that the MPE performance is lower for `beethoven1` and `beethoven2` as these pieces involve the use of the sustain pedal. While some of the DA methods vary in effectiveness for different music content, like FPDA and CORAL, overall the results of DA seem to be quite consistent and do not improve performance significantly regardless of the musical content.

7. DISCUSSION

Although the examined DA methods reduced the domain shift between `MAPS-train` and our test dataset `IDMT-PIANO-MM` (see Table 2), the MPE performance could not be improved significantly by DA. We see several possible explanations for this.

First, it should be noted that the applied method to quantify domain shift assumes that each convolutional layer of the MPE model contains only one filter, which is not given with the U-net MPE model. Further research must investigate how this discrepancy leads to a biased measurement. Yet, we expect that the computed domain shift values can

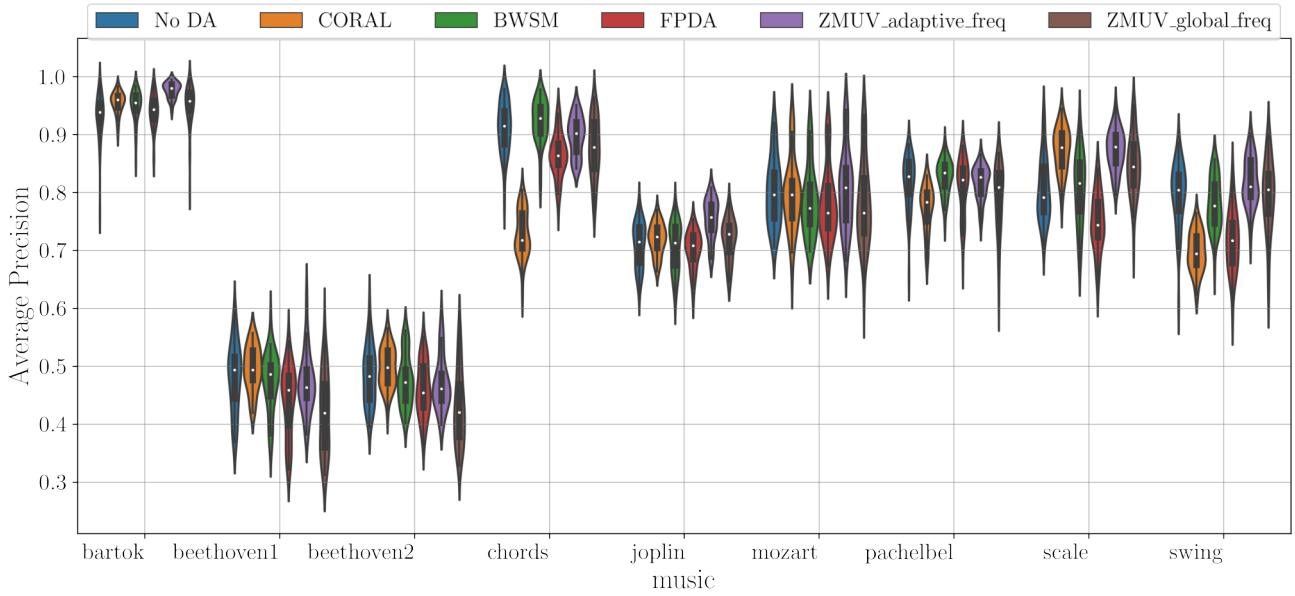

Figure 4. Performance of the MPE model on `IDMT-PIANO-MM`. The average precision score is presented for different DA methods grouped by music pieces.

still provide a general tendency.

Second, the employed MPE model might already generalize well enough to the given task. In fact, the U-net model itself can be considered as a reconstruction-based deep DA implementation as defined in [5]. The encoding procedure ensures that domain-specific features are disregarded, while the decoding part enables to attribute a feature within a domain. Therefore, it would be interesting to examine the presented DA methods for MPE models with other network architectures.

Third, the benchmark dataset `IDMT-PIANO-MM` does not provide precise offset annotations, which can introduce label noise to the frame-wise MPE evaluation.

Finally, there are further restrictions for particular DA methods. Our implementation of FPDA involves cutting the features after 16 time frames (about 0.372 s), whereas the original approach [15] keeps 10 s of data for the transformation matrix. As we reduced the size of the transformation matrix extremely, our implementation could be inaccurate. Moreover, unlike in the original paper [15] it was not possible to use recordings with identical content (denoted as "parallel data" in [13]). This requires audio data to be simultaneously captured using source and target domain devices, which is not applicable in this study. Besides, CORAL is implemented as time-independent DA since frequency patterns are only compared within one time frame. The domain-specific knowledge of time is disregarded due to buffer memory limits. As there is no reference implementation for CORAL in the audio domain to our knowledge, we cannot compare this approach to other findings. The effectiveness of adaptive ZMUV normalization is restricted by the sole dependency on recorded target data. Unlike in global ZMUV normalization, no source domain data is used to modify target data. Hence, if the amount of cached target data is too small, the DA may fail.

8. CONCLUSION

In this paper, we studied the influence of domain shift to piano MPE under microphone mismatch conditions. As our first contribution, we created and published a novel benchmark dataset of piano recordings captured with various mobile devices. In our initial experiments, we verified differences in the used recording devices using the spectrum correction coefficient method. As a second step, we quantified the domain shift between the source domain (`MAPS-train`) and different target domains of a novel benchmark dataset (`IDMT-PIANO-MM`) using the representation shift based on the Wasserstein distance between distributions of intermediate activation map values of the MPE model. We investigated in particular the performance of an MPE model based on the U-net architecture. As expected, the domain shift was greater between source and target data than between two subsets of the MAPS dataset (0.035 vs. 0.029 respectively), possibly due to different types of recording settings.

As a third step, we investigated the influence of domain shift on the MPE performance and found that the U-net model is surprisingly robust to domain shift conditions. We assume the main reason for this is that spectral peaks contain the main information for the MPE. Domain shift, however, mainly causes deviations in the overall spectral envelope of the signal, which are mostly irrelevant for the given task. Finally, we evaluated four different unsupervised DA methods in order to reduce the domain shift. The DA method BWSM was able to reduce the measured domain shift from the initial 0.035 to 0.029.

In future research, we aim to evaluate additional MPE models based on other neural network architectures, such as CRNNs or transformer models, to assess the influence of the network architecture on the robustness against domain shift.

9. ACKNOWLEDGEMENTS

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MELODY TRANSCRIPTION VIA GENERATIVE PRE-TRAINING

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ABSTRACT

Despite the central role that melody plays in music perception, it remains an open challenge in MIR to reliably detect the notes of the melody present in an arbitrary music recording. A key challenge in *melody transcription* is building methods which can handle broad audio containing any number of instrument ensembles and musical styles—existing strategies work well for *some* melody instruments or styles but not all. To confront this challenge, we leverage representations from Jukebox [1], a generative model of broad music audio, thereby improving performance on melody transcription by 20% relative to conventional spectrogram features. Another obstacle in melody transcription is a lack of training data—we derive a new dataset containing 50 hours of melody transcriptions from crowdsourced annotations of broad music. The combination of generative pre-training and a new dataset for this task results in 77% stronger performance on melody transcription relative to the strongest available baseline. [1] By pairing our new melody transcription approach with solutions for beat detection, key estimation, and chord recognition, we build Sheet Sage, a system capable of transcribing human-readable lead sheets directly from music audio.

1. INTRODUCTION

In the Western music canon, *melody* is a defining characteristic of musical composition, and can even constitute the very identity of a piece of music within the collective consciousness. Because of the significance of melody to our music perception, the ability to automatically transcribe the melody notes present in an arbitrary recording could enable numerous applications in interaction [2], education [3], informatics [4], retrieval [5], source separation [6], and generation [7]. Despite the potential benefits, reliable melody transcription remains an open challenge.

A closely-related problem that has received considerable attention from the MIR community is *melody extraction* [8–11], where the goal is to estimate the time-varying, continuous F0 trajectory of the melody in an audio mixture. In contrast, the goal of melody transcription is to output the *notes* of the melody, where a note is defined by an onset time, a pitch, and an offset time. While F0 trajectories are useful for several downstream tasks (e.g., query by humming) and more inclusive of music which does not use equal-tempered pitches, unlike notes, trajectories cannot be readily converted into formats like MIDI or scores which are more convenient for musicians.

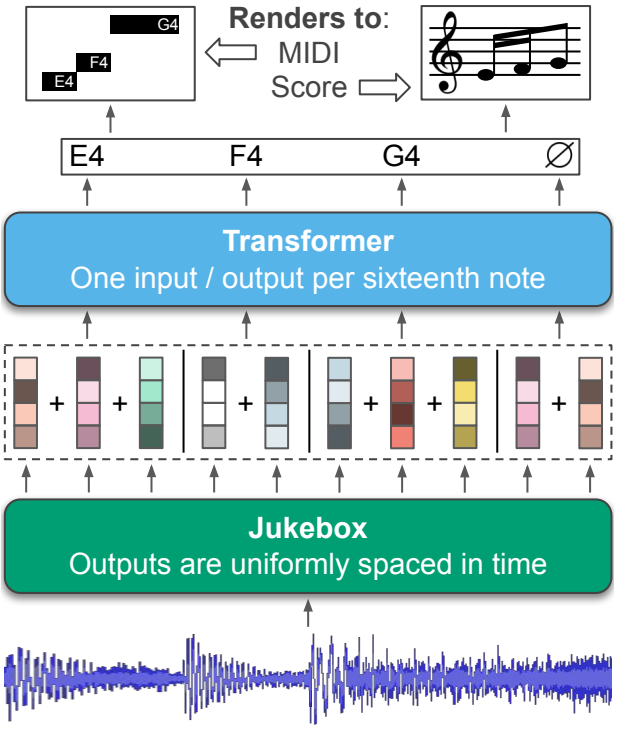

Figure 1. Our melody transcription approach involves (1) extracting audio representations from Jukebox [1], a generative model of music, (2) averaging these representations across time to their nearest sixteenth note (dashed outline—uses `madmom` [12, 13] for beat detection), and (3) training a Transformer [14] to detect note onsets (or absence thereof) per sixteenth note. Outputs can be rendered to MIDI (by mapping beats back to time) or a score.

The relative lack of progress on melody transcription is perhaps counterintuitive when compared to the considerable progress on seemingly more difficult tasks like piano transcription [15, 16]. This circumstance stems from two primary factors. First, unlike in piano transcription, melody transcription involves operating on *broad* audio mixtures from arbitrary instrument ensembles and musical styles. Second, there is a deficit of training data for melody transcription, which particularly impedes the deep learning approaches central to recent improvements on other transcription tasks. Moreover, collecting data for melody tran-

[1] Examples: `https://chrisdonahue.com/sheetsage`
Code: `https://github.com/chrisdonahue/sheetsage`

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scription is difficult compared to collecting data for tasks like piano transcription, where a Disklavier can be used to create aligned training data in real time.

To overcome the challenge of transcribing broad audio, in this work we leverage representations from Jukebox [1], a large-scale generative model of music audio pre-trained on 1M songs. In [17], Castellon et al. demonstrate that representations from Jukebox are useful for improving performance on a wide variety of MIR tasks. Here we show that, when used as input features to a Transformer model [14], representations from Jukebox yield 27% stronger performance on melody transcription (as measured by note-wise F1) relative to handcrafted spectrogram features conventionally used for transcription. To our knowledge, this is the first evidence that representations learned via generative modeling are useful for time-varying MIR tasks like transcription, as opposed to the song-level tasks (e.g. tagging, genre detection) examined in [17].

To address the data deficit for melody transcription, we release a new dataset containing 50 hours of melody annotations for broad audio which we derive from HookTheory. [2] The user-specified alignments between the audio and melody annotations in HookTheory are crude—we refine these alignments using beat detection. To overcome remaining alignment jitter, we resample features to be uniformly spaced in beats (rather than time) and pass these *beat-wise resampled* features as input to melody transcription models. This procedure has a secondary benefit of enabling simple conversion from raw model outputs to human-readable scores (Figure 1).

By training Transformer models on this new dataset using representations from Jukebox as input, we are able to improve overall performance on melody transcription by 70% relative to the strongest available baseline. A summary of our primary **contributions** follows:

- We show that representations from generative models can improve melody transcription (Section 6).
- We collect, align, and release a new dataset with 50 hours of melody and chord annotations (Section 4).
- We propose a method for training transcription models on data with imprecise alignment (Section 5.3).
- As a bonus application of our melody transcription approach, we build a system which can transcribe music audio into lead sheets (Section 7).

2. RELATED WORK

Melody transcription is closely related to but distinct from the task of melody extraction, originally referred to as predominant fundamental frequency (F0) estimation [8, 9]. Melody extraction has received significant interest from the MIR community over the last two decades (see [10, 11] for comprehensive reviews), and is the subject of an annual MIREX competition [18]. Melody extraction may be a component of a melody transcription pipeline in combination with a strategy to segment F0 into notes [19–21]—we directly compare to such a pipeline in Section 6.2.

Compared to melody extraction, melody transcription has received considerably less attention. Earlier efforts use sophisticated DSP-based pipelines [22–25]—unfortunately none of these methods provide code, though [24] provides example transcriptions which we use to facilitate direct comparison. A more recent effort uses ground truth chord labels as extra information to improve melody transcription [26]—in contrast, our method does not require extra information. Another line of work seeks to transcribe solo vocal performances into notes [27–30]. As singing voice often carries the melody in popular music, we directly compare to a baseline which firsts isolates the vocals (using Spleeter [31]) and then transcribes them.

Polyphonic music transcription is another related task which involves transcribing *all* of the notes present in a recording (not just the melody). This task has its own MIREX contest (Multiple Fundamental F0 Estimation) alongside a growing collection of supervised training data resources [7, 32–34]. The similarity of the polyphonic and melody transcription problems motivates us to experiment with representations learned by a polyphonic system—specifically, MT3 [35]—for melody transcription.

3. TASK DEFINITION

In this work, melody transcription refers to the task of converting a music recording into a *monophonic* (non-overlapping) sequence of *notes* which constitute its dominant melody. [3] More precisely, given a music waveform $\boldsymbol{a}$ of length T seconds, our task is to uncover the sequence of N notes $\boldsymbol{y} = [\boldsymbol{y}_1, \ldots, \boldsymbol{y}_N]$ that represent the melody of $\boldsymbol{a}$. For many MIR tasks, including transcription, it can be convenient to work with *features* of audio $\boldsymbol{X} = \texttt{Featurize}(\boldsymbol{a})$, rather than waveforms. Hence, a melody transcription algorithm is a procedure that maps featurized audio to notes, i.e. $\boldsymbol{y} = \texttt{Transcribe}(\boldsymbol{X})$.

Canonically, a musical note consists of an onset time, a musical pitch, and an offset time. However, in this work we disregard offsets and define a note to be a pair $\boldsymbol{y}_i = (t_i, n_i)$ consisting of an onset time $t_i \in [0, T)$ and discrete musical pitch $n_i \in \mathbb{V} = \{\text{A0}, \ldots, \text{C8}\}$. We ignore offsets for two reasons. First, accurate offsets have been found to be considerably less important for human perception of transcription quality compared to accurate onsets [36]. Second, in our dataset, a heuristically-determined offset is identical to the user-annotated offset for 89% of notes. [4]

Formally, a musical audio recording of length T seconds sampled at rate f_s is a vector $\boldsymbol{a} \in \mathbb{R}^{Tf_s}$. A featurization of audio $\boldsymbol{X} \in \mathbb{R}^{Tf_k \times d}$ is a matrix of d-dimensional features of audio, sampled uniformly at some rate $f_k \ll f_s$ (for example, $\boldsymbol{X}$ could be a spectrogram). Intuitively, the function $\texttt{Featurize} : \mathbb{R}^{Tf_s} \to \mathbb{R}^{Tf_k \times d}$ defined by

[2] https://www.hooktheory.com/theorytab

[3] Melody is difficult to precisely define—here we adopt an implicit definition based on a dataset of crowdsourced melody annotations.

[4] The specific heuristic that we use sets the offset of one note equal to the onset of the next, i.e., it assumes the melody is legato.