Improving Perceptual Quality of Drum Transcription with the Expanded Groove MIDI Dataset

Lee Callender* 1  Curtis Hawthorne* 2  Jesse Engel 2

Abstract
Classifier metrics, such as accuracy and F-measure score, often serve as proxies for performance in downstream tasks. For the case of generative systems that use predicted labels as inputs, accuracy is a good proxy only if it aligns with the perceptual quality of generated outputs. Here, we demonstrate this effect using the example of automatic drum transcription (ADT). We optimize classifiers for downstream generation by predicting expressive dynamics (velocity) and show with listening tests that they produce outputs with improved perceptual quality, despite achieving similar results on classification metrics. To train expressive ADT models, we introduce the Expanded Groove MIDI dataset (E-GMD), a large dataset of human drum performances, with audio recordings annotated in MIDI. E-GMD contains 444 hours of audio from 43 drum kits and is an order of magnitude larger than similar datasets. It is also the first human-performed drum dataset with annotations of velocity. We make this new dataset available under a Creative Commons license along with open source code for training and a pre-trained model for inference.

1. Introduction

Discriminative models predict the conditional distribution \( p(y|x) \) over labels \( y \) that correspond to an input \( x \). While classifier metrics such as accuracy, precision, recall, and F-measure scores are often used to evaluate discriminative models, decision theory highlights that the true quantity of interest is the expected utility (or cost) of the inferred labels in a downstream task (Von Neumann et al., 2007). This framework has been thoroughly explored for models such as binary classifiers and ranking systems (Parmigiani & Inoue, 2009). For example, in medical applications, the relative cost of false negatives and false positives must be carefully considered when basing decisions on the predictive outputs of a model (Dusenberry et al., 2019).

In recent years, discriminative models have increasingly been used not just for classification and decision making, but also to provide inputs for generative systems. For example, state-of-the-art Generative Adversarial Networks (GANs) often make use of attribute labels or segmentation maps to provide fine-scale control over generated images (Wang et al., 2018; Park et al., 2019; Mirza & Osindero, 2014), and text-to-speech systems make extensive use of labels from automatic speech recognition, such as graphemes, phonemes, and fundamental frequencies (Kalchbrenner et al., 2018; Shen et al., 2018; Amodei et al., 2016). While the downstream utility of these combined discriminative and generative systems is usually the perceptual quality of the final output, they are often developed separately and combined post-hoc. Contrary to this trend, recent work on piano transcription has demonstrated the value of considering downstream generation, showing that separately classifying note onsets from note persistence led to dramatic improvements in the perceptual quality of generation due to a reduction in false positive onsets (Hawthorne et al., 2018).

Here, we examine this approach of optimizing classifiers for downstream generation for the case of Automatic Drum Transcription (ADT). Our key contributions include:

- The Expanded Groove MIDI dataset (E-GMD), the first dataset to capture both expressive timing and velocity of human performances.
- Training expressive ADT models on E-GMD to predict timings, drum hit, and velocity by incorporating a separate velocity-prediction head.
- Developing a new Shuffled mixup strategy for data augmentation and regularization that effectively limits overfitting.
- Demonstrating that predicting expressive dynamics (velocity) in addition to timing generates outputs with improved perceptual quality, as determined by listening tests, despite achieving similar results on classification metrics.

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Audio samples of the dataset and examples used in the listening test are provided in the online supplement at https://goo.gl/magenta/e-gmd-examples, and the full dataset is available at https://g.co/magenta/e-gmd under the Creative Commons Attribution 4.0 International (CC BY 4.0) license.

2. Related Work

The recent work of Wu et al. (2018) provides a comprehensive overview of ADT and includes evaluation of current state of the art methods. While there has been a large collection of studies published over ADT in recent years (Vogl et al., 2018; Choi & Cho, 2019; Cartwright, 2018; Wu & Lerch, 2018; Southall et al., 2018a,b; Ueda et al., 2019), most ADT research has maintained a focus on classifier metrics to assess quality.

Of the approaches that have explored deep learning (Vogl et al., 2018; Choi & Cho, 2019; Cartwright, 2018; Southall et al., 2018a), research is still fairly new given the large data required to effectively produce a model. As annotating drums is still a fairly manual task, most datasets for ADT are relatively small in size and resource intensive to create. This has lead to new research into solving that problem, including unsupervised approaches (Choi & Cho, 2019; Wu & Lerch, 2018) and the creation of synthetic datasets (Choi & Cho, 2019; Vogl et al., 2018; Cartwright, 2018; Miron et al., 2013).

Given the difficulty of ADT and the limited datasets available, the overwhelming majority of ADT research has focused on ADT with the classification of 3 primary drum hits: Kick Drum, Snare Drum, Hi-hat (KD, SN, HH) (Dittmar & Gärtner, 2014b; Lindsay-Smith et al., 2012; Wu & Lerch, 2015; Vogl et al., 2016; 2017a; Stables et al., 2016; Southall et al., 2017a). A handful of datasets contain annotations beyond the 3 standard hits, however the set of drum hits is not standardized, with each dataset containing a varied collection of drum hits (Vogl et al., 2018; Cartwright, 2018; Dittmar & Uhle, 2004).

Velocity has sometimes been considered during ADT tasks. For example, in DrummerNet (Choi & Cho, 2019), velocity is used as a probability of hit for peak-picking. However, velocity is not predicted as part of overall model output. To the best of our knowledge, our work is the first model that directly predicts velocity values and evaluates the perceptual quality of resynthesized outputs.

3. Datasets

Only a handful of public datasets are available for ADT, and many have limited size and diversity. An even smaller subset of datasets contain human performances, and no public datasets contain human performances with velocity annotations (Cartwright, 2018; Wu et al., 2018; Vogl et al., 2018). Reasons for these limitations include the tedious nature of generating labels for real drum performances and restrictions around licensing and intellectual property.

The difficulty of annotating real drum performances has inspired some recent studies to generate their own synthetic datasets. These datasets are commonly generated by taking a collection of MIDI (Music Instrument Digital Interface, the industry standard format for symbolic music data) drum performances and synthesizing audio via drum samples (Miron et al., 2013; Vogl et al., 2018; Cartwright, 2018). Only one of these datasets is public (Vogl et al., 2018), and it does not contain velocity annotations.

Table 1 compares several public datasets, including E-GMD. Of these datasets, we decided to use IDMT-SMT (Dittmar & Gärtner, 2014a) and ENST (Gillet & Richard, 2006) in our evaluations because of their commonality in prior studies. We opted not to use MDB Drums (Southall et al., 2017b) because of its small size and did not use the dataset from Vogl et al. (2018), which we refer to as TMIDT, because the licensing of its source material was ambiguous. We also did not use RBMA13 (Vogl et al., 2017b) because the tracks included music in addition to drums, and we focused on transcribing only solo drumming.

E-GMD has many different annotated hits. For evaluation and listening tests, we group the annotated hits down to a 7 hit classification task, as shown in Table 2.

3.1. IDMT-SMT

IDMT-SMT contains only the 3 standard drum hits (KD, SN, HH), and contains 4 different drum kits. The dataset uses relatively simple drum patterns and contains audio and ground truth hit annotations. One drum kit is an acoustic kit that was recorded with varying velocities, however the ground truth annotations do not consider velocity and only
改善鼓谱转录感知质量的扩展Groove MIDI数据集

3.3. 扩展Groove MIDI数据集

我们引入了一个扩展的Groove MIDI数据集（E-GMD），我们将Groove MIDI数据集（GMD）称为扩展的Groove MIDI数据集（E-GMD）。GMD是一个包含人类鼓击声的音乐数据集，原用于Roland TD-11电子鼓套件，最初是为了生成鼓谱合成开发的（Gillick et al., 2019）。MIDI信息包含事件，如音符，关联乐器、时间及速度。

GMD包含13.6小时，1,150个MIDI文件，以及22种不同类型的鼓。数据集通过将合成输出与TD-11对齐以2ms的误差。使用Roland TD-17，可被作为TD-11（不再生产）的近似版本用于鼓击声。

为了使数据集适用于ADT，我们扩展了它通过在Roland TD-17上记录43个鼓击套件。TD-17是一个获奖的电子鼓套件，适用于电子（如808、909）到声学声音的转换。额外的鼓击是一次44.1kHz，24位数，并且在2ms内对原始MIDI文件对齐。使用Roland TD-17，一个近似版本的TD-11（不再生产）使用在原始Groove数据集，用于准确再现初始性能的细微差别。

我们实现半自动过程来系统性地记录TD-17的鼓击声。

3.2. ENST

ENST数据集是由三人专业鼓手表演的三套不同节奏的电子鼓击声，每人使用手鼓、鼓棒、刷子，或鼓槌。每个序列产生一个鼓声的组合。

数据集包含单个乐器击打声的短句和鼓击声，伴有或不伴有额外的伴奏。注解包括用于20个不同鼓击声的标签。虽然ENST的性能被记录，但再无速度注解。

在我们的实验中，我们使用了隔离的鼓击声进行实验（标记为“减一”），并将其用于在未使用的鼓声中进行比较。这些隔离的鼓击声制作64个各61s平均长度的鼓击声，并作为一个小时的总长度。我们使用所有64个鼓击声。剩下的数据集（单个打击声，图案）被忽略了。

我们考虑了鼓击声的类型和时间。其他的鼓击声使用合成鼓。数据集包含原始的鼓击声的音频，以及3个击鼓声的音频。我们使用音频的音频用于评估，并使用整个数据集，因为它受限制。

| E-GMD HITS         | 7 HIT | 3 HIT |
|--------------------|-------|-------|
| KICK DRUM          | KD    | KD    |
| SNARE DRUM         | SD    |       |
| SNARE RIM          |       |       |
| CROSS-STICK        |       |       |
| CLAP               |       |       |
| TOM 1              | TT    |       |
| TOM 1 RIM          |       |       |
| TOM 2              |       |       |
| TOM 2 RIM          |       |       |
| TOM 3              |       |       |
| TOM 3 RIM          |       |       |
| OPEN HI-HAT BOW    | HH    |       |
| CLOSED HI-HAT BOW  | HH    |       |
| PEDAL HI-HAT BOW   |       |       |
| TAMBOURINE         |       |       |
| CRASH 1 BOW        | CY    |       |
| CRASH 1 EDGE       |       |       |
| CRASH 2 BOW        |       |       |
| CRASH 2 EDGE       |       |       |
| RIDE BOW           | RD    |       |
| RIDE EDGE          |       |       |
| RIDE BELL          | BE    |       |
| COW BELL           |       |       |

表格2：为E-GMD的鼓击声层次。3和7击的组合被用于在评估和倾听测试中。

3.3. 扩展Groove MIDI数据集

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GMD包含13.6小时，1,150个MIDI文件，以及22种不同类型的鼓。数据集通过将合成输出与TD-11对齐以2ms的误差。使用Roland TD-17，一个近似版本的TD-11（不再生产）使用在原始Groove数据集，用于准确再现初始性能的细微差别。

为了使数据集适用于ADT，我们扩展了它通过在Roland TD-17上记录43个鼓击套件。TD-17是一个获奖的电子鼓套件，适用于电子（如808、909）到声学声音的转换。额外的鼓击是一次44.1kHz，24位数，并且在2ms内对原始MIDI文件对齐。使用Roland TD-17，一个近似版本的TD-11（不再生产）使用在原始Groove数据集，用于准确再现初始性能的细微差别。

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We maintained the same train, test and validation splits across sequences that GMD had. As each kit was recorded for every sequence, we see all 43 kits in the train, test and validation splits. The count of hits across all splits is shown in Table 4.

Table 3. E-GMD unique sequences, total sequences, and duration in hours by split.

| SPLIT       | UNIQUE SEQ | TOTAL SEQ | DUR  |
|-------------|------------|-----------|------|
| TRAIN       | 819        | 35,217    | 341.4H |
| TEST        | 123        | 5,289     | 50.9H  |
| VALIDATION  | 117        | 5,031     | 52.2H  |
| TOTAL       | 1,059      | 45,537    | 444.5H |

Table 4. E-GMD hit counts across splits in thousands. We show the counts for the seven hit grouping of E-GMD, seen in Table 2, for brevity.

| HIT | TRAIN | TEST | VALIDATION |
|-----|-------|------|------------|
| KD  | 2,181k| 319k | 343k       |
| SD  | 3,477k| 468k | 533k       |
| HH  | 3,045k| 553k | 518k       |
| TT  | 805k  | 98k  | 171k       |
| RD  | 1,260k| 105k | 84k        |
| BE  | 191k  | 9k   | 21k        |
| CY  | 122k  | 10k  | 27k        |

The online supplement includes examples of different sequences and kits at https://goo.gl/magenta/e-gmd-examples. The dataset is available at https://g.co/magenta/e-gmd under the Creative Commons Attribution 4.0 International (CC BY 4.0) license.

4. Model

We base our model on Onsets and Frames (Hawthorne et al., 2018) and adapt its note and velocity prediction capabilities to drum hit and velocity predictions. We call our new model OaF-Drums.

We use only the onset and velocity stacks of the network, as illustrated in Figure 1, because drum hits do not sustain like piano notes and so we do not require the frame or offset predictions. Complete network details are given in the Supplement.

For log mel-spectrogram creation, we increased the audio sample rate from 16 KHz to 44.1 KHz, the number of bins from 229 to 250, and shortened the hop length from 512 to 441 samples, resulting in frames with a 10ms width (Vogl et al., 2018). We found the higher sample rate improved the model’s ability to process events with high-frequency content like cymbal crashes, and the higher frame resolution was important for predicting events that repeated rapidly, such as drum rolls. The resulting higher resolution network required more memory during training, so we also switched from processing batches of 20-second segments to 12-second segments.

For labels, we forced onset labels to occupy a single frame instead of being spread across 30ms of frames as they are in the original piano model. This also helped improve accuracy for rapidly repeating events. Finally, we added a 0.5 weight multiplier to the velocity loss to prioritize correct hit recognition during training.

We found that overfitting on the training data was a significant concern. The initial manifestation of this problem was that the trained model would transcribe only the first and last few seconds of an evaluation sequence. We suspect this was due to the bidirectional LSTM layer memorizing drum sequences that are simpler than the piano sequences this architecture was originally designed for (8 hits instead of 88 notes). Also, even though our training data has 35,217 audio examples due to our many drum kits, there are only 1,059 unique drum hit sequences.

To prevent overfitting, we used the standard techniques of reducing model capacity and adding dropout (Merity et al., 2017). We decreased the size of the bidirectional LSTM layer from 128 to 64 units and added dropout at a rate of 50% to the outputs of the LSTM cells, but this alone was insufficient.

We also used a form of mixup (Zhang et al., 2017) for data augmentation and regularization. We created 500,000 training examples by randomly selecting pairs of examples from the training set, repeating the shorter of the examples until it was as long as the longer one, and then mixing their audio samples and underlying MIDI data together (prior to spectrogram or piano roll calculation) to form a new example, which is then split into 12-second chunks. This improved evaluation scores, but we still saw strongly divergent train/evaluation curves.

To create further diversity during training, we split those 500,000 examples into 1-second chunks. Then, at training time we splice together random chunks into a 12-second example. We call this technique Shuffled mixup and it is
what we used when training our final model. With this configuration, we no longer saw diverging train/evaluation curves. A comparison of these different techniques can be seen in Table 5.

Table 5. Data augmentation and regularization ablation study. Results are F-measure scores calculated on E-GMD Validation, E-GMD Test, IDMT, and ENST. Shuffled mixup is the technique used when training our final OaF-Drums model. Training setup for the other methods is otherwise the same except that training was stopped after approximately 250k steps.

| Model           | Valid | Test | IDMT | ENST |
|-----------------|-------|------|------|------|
| Shuffled mixup  | 88.71 | 83.40| 85.72| 76.89|
| mixup           | 79.48 | 69.11| 47.44| 62.27|
| Unmodified      | 74.66 | 63.07| 52.74| 67.35|

After resolving the issue of overfitting to sequences, we also performed a coarse hyperparameter search and discovered that using a smaller convolutional stack prevented the model from overfitting to the particular characteristics of the drum sets in our training dataset. We reduced the number of filters in the convolutional layers from 32/32/64 to 16/16/32 and decreased the units in the fully connected layer from 512 to 256.

Our final model was trained with a batch size of 128 for 569,400 steps on 16 TPUv3 cores, which took about 3 days. We used the Adam optimizer with an initial learning rate of 1e−4 and an exponential learning rate decay, reducing by a factor of .98 every 10,000 steps. No early stopping strategy was used other than seeing that the train and evaluation curves had stabilized.

Code for training and evaluation along with a pre-trained model for inference is available on GitHub: https://goo.gl/magenta/onsets-frames-code.

5. Evaluation

Table 6 compares classifier scores for a variety of models and datasets. F-measure (also known as F1 score) is used as the evaluation metric, with a 50ms tolerance window of ground truth annotations for detected onsets as is consistent with the prior studies. We use the mir_eval package for metrics calculation (Raffel et al., 2014).

We compare against the two other models that were also used in the listening study. These models are ADTLib\(^3\) and DrumTranscriptor\(^4\) (DT), which are from Southall et al. (2017a) and Vogl et al. (2018) respectively. ADTLib is trained on the standard 3 hit ADT task, while DrumTranscriptor is capable of transcribing 18 hits.

The public implementation of DrumTranscriptor is an ensemble 5 models trained on 5 different datasets: TMIDT, TMIDT balanced, ENST, MDB, and RBMA. We refer to this as DrumTranscriptor Ensemble (DT-Ensemble). This contrasts with the single DrumTranscriptor model (DT) in the paper, the best variant of which is trained only on TMIDT. We use DT-Ensemble for our listening study as it outperforms the DT model.

We train OaF-Drums on the E-GMD dataset and evaluate it on IDMT (3-hit standard) and ENST (multi-hit standard) for comparisons to other models.

5.1. IDMT Evaluation

IDMT was chosen primarily due to its consistent use in prior studies. It contains only the standard 3 hits (KD, SN, HH). In order to evaluate OaF-Drums in the simpler ADT task, we grouped the 7 possible drum hit predictions into the 3 hits. This grouping is shown in Table 2. This is somewhat different than other models we compare against that were trained to predict only those 3 hits and ignore other audio events. We believe this comparison is reasonable because both training/evaluation methods incorporate a priori knowledge of what hits need to be predicted. This is yet another example of how different hit mapping strategies makes ADT evaluation difficult. Ultimately, we believe any comparison of models needs to incorporate a perceptual component as we do in the Listening Test in Section 6.

We evaluated against ADTLib and DT-Ensemble for IDMT. DT-Ensemble used the same 7 hit grouping that OaF-Drums did. ADTLib only uses the 3 hit grouping and was trained on ENST only considering the standard 3 hits (ENST-3). The IDMT results for ADTLib, OaF-Drums and DT-Ensemble are shown in Table 6. All models perform rather well, with DT-Ensemble having the best score followed by OaF-Drums.

A full IDMT evaluation against the state of the art models reviewed in (Wu et al., 2018) is in the Supplement. OaF-Drums has the 3rd best average F-measure of the 11 models. All the other models perform the standard 3 hit classification like ADTLib. The competitive score for OaF-Drums adds confidence that it performs well in the simpler ADT task, especially considering the model has been trained for more complex classification in the number of drum hits and added velocity prediction.

5.2. ENST Evaluation

We evaluate against ENST to compare our model in the multi-hit scenario, beyond the typical 3 hit ADT task. There are only a few models that attempt to model beyond 3 hits (Dittmar & Uhle, 2004; Vogl et al., 2018; Choi & Cho, 2019; Cartwright, 2018), and there is no standardization of
Table 6. F-measures and listening study results from Section 6. Note the OaF-Drums model wins the listening study by a significant margin despite achieving comparable classification results to other models. The asterisk on DT-Ensemble* highlights that the model is actually an ensemble of 5 models trained on 5 different datasets. We use the DT-Ensemble in the listening study as it outperforms the single DT model. OaF-drums is the only model that predicts velocities, so it is the only model to be evaluated on E-GMD velocity labels. Since the various models are trained on different datasets, we compare classifier scores across a range of datasets, and perform the listener studies on the Loop Loft dataset, on which none of the models have been trained.

| MODEL        | TRAINING DATASET(S) | IDMT  | ENST  | E-GMD  | E-GMD (VEL) | LOOP LOFT |
|--------------|---------------------|-------|-------|--------|-------------|-----------|
| OaF-DRUMS    | E-GMD               | 85.27 | 76.89 | 83.40  | 61.70       | 919       |
| DT-ENSEMBLE* | TMIDT(-BAL), MDB, ENST, RBMA | 91.49 | 82.96 | 64.98  | ×           | 677       |
| DT           | TMIDT               | ×     | 68.00 | ×      | ×           | ×         |
| ADTLib       | ENST-3              | 83.12 | ×     | ×      | ×           | 372       |

evaluation for multi-hit models. There are also a very small number of public datasets that have multi-hit annotation and within those datasets there is inconsistency in number and type of drum hits used.

Of the multi-hit models, Vogl et al. (2018) appear to have the best generalized performance across different datasets, and a public model implementation (DT-Ensemble) was available for additional inference for the listening study. Therefore, we elected to use that work as a proxy for the current state of the art in the multi-hit scenario.

Multi-hit comparison is a non-trivial task since DT-Ensemble is capable of classifying 18 different drum hits, which contrasts to the 25 different drum hits labeled in E-GMD, and the 20 different drum hits labeled in ENST. While there are some consistent mappings between drum hits in each domain, for example, KD, there is a lot of variation and ambiguity in mapping other categories such as cymbals and toms. We elected to evaluate the multi-hit task on a reduction of seven hits shown in Table 2. This seven-hit mapping is comparable to the eight-hit model of DT and DT-Ensemble because Clave (the eighth kind of hit) is not used in either our training or evaluation datasets. DT-Ensemble never predicted Clave during evaluation.

The F-measure results for ENST are shown in Table 6. OaF-Drums outperforms DT, but both are outperformed by DT-Ensemble, which is expected since DT-Ensemble is trained on ENST. The F-measure results broken down by drum hit are shown in Figure 2.

When broken down by hit, the F-measure results reveal stark contrasts in performance for different hits. Events such as Bells (BE) are rare and have significant variation between datasets, leading to poor generalization of models not trained on the dataset (OaF-Drums and DT for ENST, and DT-Ensemble for E-GMD).

Some attempts have been made to combat this behavior. Applying different weights to onsets in the loss function can help in some cases (Cartwright, 2018; Vogl et al., 2017), but it doesn’t appear effective in the cases of extremely sparse onsets. A more promising approach would be to re-balance the dataset to a more even distribution of onsets, which is explored with the TMIDT dataset in (Vogl et al., 2018). The balanced dataset carried a trade-off in that model however, since per hit F-measures were much more even but overall F-measure notably decreased.

5.3. E-GMD Evaluation

As a final test, we evaluate OaF-Drums and DT-Ensemble against E-GMD. We elect to reduce all drum hit classes down to the same seven classes used in the ENST test as shown in Table 2. The results of E-GMD are shown in Table 6. The F-measure scores for both test and validation are shown in the Supplement. Not surprisingly, OaF-Drums outperforms DT-Ensemble. While OaF-Drums did not train on any of the sequences in the E-GMD test subset, the training dataset did have audio from the same drum kits.

We also evaluate OaF-Drums performance using an F-measure score that includes velocity predictions as described in (Hawthorne et al., 2018). We only evaluate OaF-Drums on velocities, as the other models do not predict velocity labels. Results are again shown in Table 6. Results for both test and validation splits are shown in the Supplement.

Across all datasets, we see that OaF-Drums performs very competitively in an F-measure comparison. This is a good sign of generalization for the model, that it can consistently perform well across datasets not seen during training.

6. Listening Test

To measure the perceptual quality of our transcription model, we conducted a listening test where raters compared synthesized transcriptions to original recordings. We opted not to use any samples from the standard transcription datasets so that no model would have a particular advantage, and instead
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Figure 2. The F-measure results per hit on ENST and E-GMD test. The ordering of bars from left to right is OaF-Drums, DT-Ensemble, DT for ENST and OaF-Drums, DT for E-GMD test. DT-Ensemble included ENST in its training set while OaF-Drums and DrumTranscriptor did not. Events such as Bells (BE) are rare and have significant variation between datasets, leading to poor generalization of models not trained on the dataset (OaF-Drums and DT for ENST, and DT-Ensemble for E-GMD).

We used 496 examples drawn from a commercial drum loop set (Loop Loft)\(^5\). Transcription model outputs were synthesized using FluidSynth\(^6\) and the SGMv2.01-Sal-Guit-Bass-V1.3 SoundFont\(^7\). We also decided to focus on comparing models with 7 or fewer output classes because that made it clear how to define a consistent set of General MIDI instruments for synthesis. We mapped all model outputs to the following General MIDI instruments: 36 (Bass Drum 1), 38 (Acoustic Snare), 42 (Closed Hi Hat), 47 (Low-Mid Tom), 49 (Crash Cymbal 1), 51 (Ride Cymbal 1), 53 (Ride Bell).

Figure 3. Results of our listening tests, showing the number of times each model won in a pairwise comparison. Black error bars indicate estimated standard deviation of means.

Table 7 shows the results of comparing our model with and without velocity predictions and clearly demonstrates the perceptual importance of velocity.

A Kruskal-Wallis H test of the ratings showed that there is at least one statistically significant difference between the models: \(\chi^2(2) = 559.19, p < 0.001 \left(7.0846e-121\right)\). A post-hoc analysis using the Wilcoxon signed-rank test with Bonferroni correction showed that there were statistically significant differences between all model pairs with \(p < .001/6\).

The online supplement includes examples of listen-
Table 7. Listening test results comparing output of the E-GMD 8 model with velocity predictions and with velocity fixed to a constant level.

| Model                  | Number of wins |
|------------------------|----------------|
| OAF-Drums w/ velocity  | 919            |
| OAF-Drums w/o velocity | 456            |

ing test comparisons at https://goo.gl/magenta/e-gmd-examples.

7. Conclusion and Future Work

In this work we explored improving perceptual quality in ADT. We introduced the Expanded Groove MIDI Dataset and use the included velocity annotations to train an OaF-Drums model with added velocity predictions. Despite achieving similar results on classification metrics, we showed that multi-hit velocity prediction is well-aligned to the downstream task of generating audio, giving significant improvements in perceptual quality as determined by listening tests.

This work also highlights the value of listening studies in evaluating transcription systems, as an example of classifier outputs as inputs to generative systems. Incorporating such studies into the standard suite of classification metrics has the potential to expand the downstream applications of ADT and provide a fair comparison of models between different datasets and architectures.

Future work could include better representation of more drum hits and combining this model with a pitched automatic music transcription model for full music ensemble transcription.

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Supplement

Table 8. F-measure performance against IDMT, showing the average, and per-instrument performance. The table is sorted in order of best average F-measure performance. Scores for models other than OaF-Drums are from the "eval cross" experiment described in (Wu et al., 2018).

| Model        | AVG | KD  | SN  | HH  |
|--------------|-----|-----|-----|-----|
| NMFD         | 90.25 | 95.87 | 83.41 | 91.47 |
| SANMF        | 86.53 | 96.40 | 71.70 | 91.50 |
| OaF-DRUMS    | 85.27 | 90.21 | 78.82 | 85.87 |
| GRUTS        | 85.14 | 92.49 | 70.30 | 92.64 |
| TANH         | 84.69 | 96.69 | 69.38 | 87.99 |
| LSTM         | 83.12 | 96.16 | 70.24 | 82.95 |
| PFNMF        | 83.02 | 94.78 | 76.13 | 78.15 |
| RNN          | 80.92 | 88.82 | 61.14 | 92.78 |
| ReLU         | 80.54 | 91.47 | 58.97 | 91.29 |
| AM1          | 79.69 | 95.91 | 81.16 | 62.00 |
| AM2          | 79.48 | 92.45 | 78.35 | 67.63 |

Table 9. F-measure performance against E-GMD validation and test.

| Model        | Validation | Test |
|--------------|------------|------|
| OaF-DRUMS    | 88.71      | 83.40 |
| DT-ENSEMBLE  | 64.07      | 63.98 |

Table 10. F-measure performance including velocity prediction accuracy against E-GMD validation and test. Only OaF-Drums scores are calculated because it is the only model that predicts velocity.

| Model        | Validation (Velocity) | Test (Velocity) |
|--------------|-----------------------|-----------------|
| OaF-DRUMS    | 64.97                 | 61.70           |
Figure 4. The F-measure results per hit on E-GMD validation splits. The ordering of bars from left is OaF-Drums, DT-Ensemble.

Table 11. Onset prediction architecture

| Layer                  | Size     | Filters | Stride |
|------------------------|----------|---------|--------|
| Log Mel Spectrogram    | 250 bins |         |        |
| Conv                   | 16       | 3x3     | 1x1    |
| BatchNorm              |          |         |        |
| Conv                   | 16       | 3x3     | 1x1    |
| BatchNorm              |          |         |        |
| MaxPool                | 1x2      | 1x2     |        |
| Dropout                | Keep 25% |         |        |
| Conv                   | 32       | 3x3     | 1x1    |
| BatchNorm              |          |         |        |
| MaxPool                | 1x2      | 1x2     |        |
| Dropout                | Keep 25% |         |        |
| Dense                  | 256      |         |        |
| Dropout                | Keep 50% |         |        |
| Bidirectional LSTM     | 64       |         |        |
| LSTM Dropout           | Keep 50% |         |        |
| Dense                  | 88       |         |        |
| Sigmoid Cross Entropy  |          |         |        |
Table 12. Velocity prediction architecture

| Layer               | Size     | Filters | Stride |
|---------------------|----------|---------|--------|
| LOG MEL SPECTROGRAM | 250 bins | 3x3     | 1x1    |
| CONV                | 16       | 3x3     | 1x1    |
| BATCHNORM           |          |         |        |
| CONV                | 16       | 3x3     | 1x1    |
| BATCHNORM           |          |         |        |
| MAXPOOL             | 1x2      | KEEP 25%| 1x2    |
| DROPOUT             |          |         |        |
| CONV                | 32       | 3x3     | 1x1    |
| BATCHNORM           |          |         |        |
| MAXPOOL             | 1x2      | KEEP 25%| 1x2    |
| DROPOUT             |          |         |        |
| DENSE               | 256      | KEEP 50%|        |
| DROPOUT             |          |         |        |
| DENSE               | 88       |         |        |
| **MEAN SQUARED ERROR** |          |         |        |