Musical Structure in Irish Traditional Tunes

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1 Introduction

Most Irish traditional folk dance music contains two musical themes; the tune begins with one musical theme which is usually repeated, then progresses to another theme with similar musical structure and motives, which is usually also repeated. The first section is typically called the A section while the second is called the B section. Our goal is to understand, at a quantitative level, the musical relationship between A sections and B sections. See fig. 1 for an example.

In working towards this goal, we need to understand both the relationship between the A and B sections of a given folk song as well as the differences between A and B sections of the tunes in general. In the long term we wish to, given an A section, automatically generate a musically appropriate B section.

2 Dataset

We are using the tunes dataset from The Session [4]. The Session is an online community of people who are interested in playing Irish folk music and cataloguing traditional Irish tunes for others to learn. These tunes include various dance forms, such as jigs, reels, waltzes, and slides. Available on their website is a set of roughly 21,000 dance tune settings in ABC notation, a human-readable symbolic music data format in plain text. The ABC files are easily parsed and manipulated symbolically for feature extraction.

3 Feature Extraction

First we select from our dataset tunes which have the standard form of an A and a B section. We consider only tunes with a number of bars in $\{16, 32, 64\}$: an individual A or B section usually has 8 or 16 measures, or 16 or 32 after manually reduplicating out music that was contained in repeat signs. We want to restrict to tunes that split evenly into two sections (e.g. not three sections, which could mean ABC, ABA, etc.).

After splitting tunes into A and B sections, we turn our attention to feature extraction. Our dataset is loosely in the form of sequences of pitches representing melodies. However, as tunes may have different lengths, we need to generate a feature vector of fixed length.

We define an n-gram as an ordered list of (in our case) n pitches of notes in a melody, ignoring accidentals. In total, we created three different feature vector designs.

1. Record counts of all 1- and 2-grams.
2. Split melodies by measure into eighths and store counts of all 1- and 2-grams separately for each measure.
3. Use the features from (2), also adding counts of notes of particular rhythmic length.

Since these feature vectors have nearly 2,000 components, before further processing, we used PCA to reduce the number of components. This helped make metric learning computationally more feasible.

Figure 1: "Cooley's (reel)", an example of a traditional Irish tune from The Session [4]. This reel has the standard form of an 8-bar A section which is repeated, then an 8-bar B section which is also repeated. The sections are labeled in the notation above. Notice how the A and B sections contain distinct melodic lines, but still have musical similarity. For example, they end with the same $2\frac{1}{2}$ bar ascending-then-descending motif.

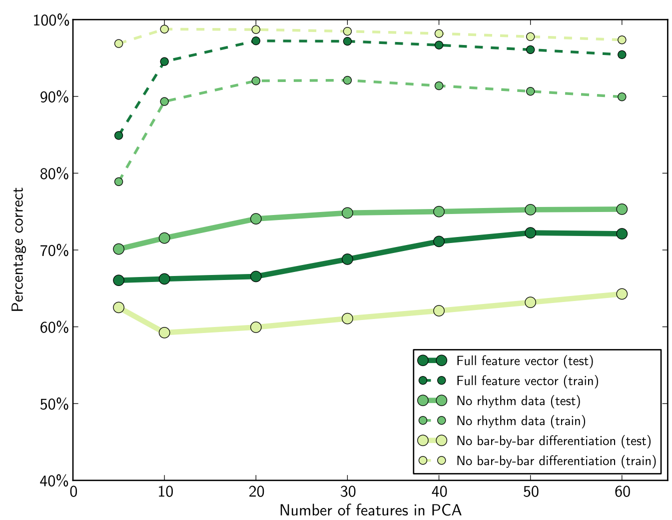


Figure 2: Accuracy of running our SVM classifier to classify musical phrases as either A or B sections. The performance on the testing dataset with various feature vector designs is shown with solid lines, and the performance on the original training set is shown in dotted lines.

4 SVM Classifier

Using our labeled pool of A and B sections, we used an SVM with Gaussian kernel to attempt to classify a given segment of a tune as an A section or a B section. We used 8-fold cross-validation, and experimented with our three different feature vectors and various numbers of PCA components. To train the SVM, we used the relevant Scikit-learn libraries [3].

Our SVM classification results are presented in fig. 2. For all three feature vector designs, performance on the test set generally improved when we kept a greater number of features when running PCA on the data. Accuracy on the training sets was much better than the testing sets—probably, this is due to overfitting the SVM to the particular training sets in each case. Even in the cases where we kept a high number of features, there is always a sizeable gap in performance on the testing set compared to the training set.

The feature vector design that gave us the least difference between training and testing performance (so probably represents the feature vector design with the least overfitting) is the "no rhythm data" feature vector, that contains pitch n-gram counts specific to each bar of the tune but not overall counts of notes with particular rhythmic values. Interestingly, the full feature vector with rhythm information caused the SVM classifier to perform worse. We believe this is because the corresponding A and B sections of most tunes may have different melodic figures, but if they are to have reasonable stylistic similarity they are likely to have similar rhythm value counts (for example, a reel whose A section is mostly eighth notes is likely to have a B section which contains mostly eighth notes). Meanwhile, having bar-by-bar differentiation of features understandably greatly improved performance—we believe this is a consequence of how in many tunes, the last bars of the A and B sections contain nearly the same notes. Thus our SVM might have learned to give greater weighting to the musical features of earlier bars, which are likely to be distinctive to A and B sections.

5 Metric Learning Problem Formulation

We also want to learn what makes the A and B sections of a particular tune musically related. We attempt to learn a metric $d(x, y)$ where, if $x, y \in \mathbb{R}^n$ are the feature vectors corresponding to the A and B sections of a tune, $d(x, y)$ should be small. For this task, we use the Mahalanobis metric, given by

$$d(x, y) = \|x - y\|_M = \sqrt{(x - y)^T M (x - y)}$$

for $M \in \mathbb{R}^{n \times n}$ positive semidefinite, and attempt to learn a suitable value of M.

Usually, in metric learning, one learns a metric by supplying both pairs of points $(x^{(i)}, x^{(j)}) \in \mathcal{S}$ that are similar and should have small distance, and points $(y^{(i)}, y^{(j)}) \in \mathcal{D}$ that are dissimilar and should have large distance. We then solve the following optimization problem for M (from [5]):

$$\begin{aligned} \text{minimize:} \quad & \sum_{(x^{(i)}, x^{(j)}) \in \mathcal{S}} \left\| x^{(i)} - x^{(j)} \right\|_M^2 \\ \text{subject to:} \quad & \sum_{(y^{(i)}, y^{(j)}) \in \mathcal{D}} \left\| y^{(i)} - y^{(j)} \right\|_M^2 \geq 1, \\ & M \succeq 0. \end{aligned}$$

However, in our problem, it is unclear how to select pairs of A and B sections that are dissimilar. Intuitively, one might argue that the A and B sections of different tunes should be dissimilar. However, two arbitrary tunes may be variations of each other, and hence have A and B sections that are related.

Note that by simply removing the dissimilarity constraint results in an optimization problem whose optimal value M is the zero matrix. Instead, we enforce $\det M = 1$ as a reasonable-seeming regularity constraint. We do this by noting that $\det M$ is concave and so $(\det M)^{1/n} \geq 1 \Leftrightarrow \det M \geq 1$ is a convex constraint [1]. Then, the optimization problem,

$$\begin{aligned} \text{minimize:} \quad & \sum_{k=1}^{m} \left\| x^{(k)} - y^{(k)} \right\|_M^2 \\ \text{subject to:} \quad & M \succeq 0, \\ & (\det M)^{1/n} \geq 1, \end{aligned}$$

where m is the number of training examples, produces M with $\det M = 1$, as the objective function scales with the determinant of M.

6 Metric Learning Implementation and Results

After using PCA to reduce our feature vectors to $n = 35$ components, we applied this method using 8-fold cross-validation to learn such a metric d. We used CVX to solve the optimization problem that determines M [2]. To evaluate the success of our metric, we consider the following problem:

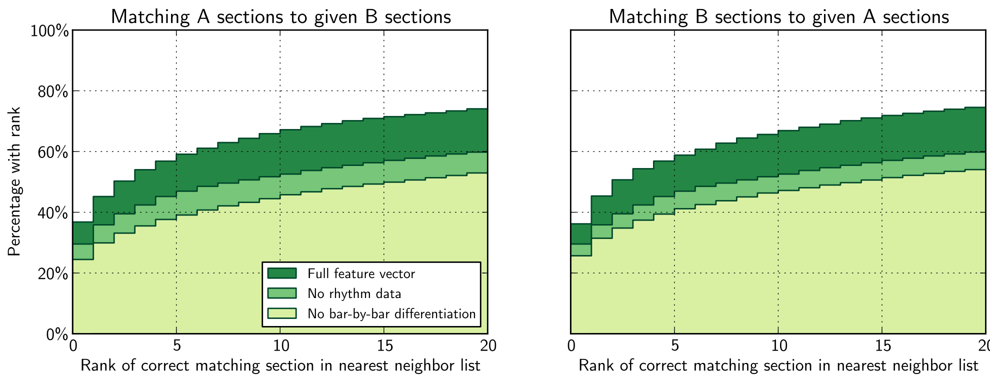


Figure 3: Results of metric learning-based matching algorithm, showing the percentage of tune sections whose matching other section appeared at a given rank in a ranked list of nearest neighbors by the learned metric. For example, the first column in the left chart represents the percentage of B sections whose matching A section was the very closest by the metric out of all possible other A sections. Here the full feature vector with rhythm information gave by far the best performance.

> Split apart the A and B sections of our test data ($\approx$ 1000 tunes). For each A section, order all the B sections by increasing distance from this A section (under the metric d). Record the rank in this list of the actual corresponding B section. Ideally, the actual B section would be the first element of this list, closest to this A section. Alternatively, we could match an A section to a given B section.

See fig. 3 for a cumulative histogram of our results. If we were to randomly guess the closest B section, we would expect the rank of the correct B section to be 1 with probability 0.1%. In our results, the correct B section was the first ranking option 37% of the time. Moreover, the correct B section was in the top 10% of the ranking 93% of the time. We conclude that there is a significant amount of information shared between A sections and B sections, and the Mahalanobis metric we learned is able to identify some of the musical similarities.

7 Composition

Now that we have shown the viability of our metric, we can use it to try to, given an A section, compose a musically related B section. We employed a simple algorithm:

1. Select a specific tune, and split it into its A and B sections.
2. Randomize a B section (b_{cur}) using the rhythm of the A section.
3. Repeat n times:
   - For every $i \in \{1, \ldots, k\}$:
     - Generate b_i by randomly making pitch edits to b_{cur}.
   - Set $b_{cur} := \arg\min_{b_i} \; d(b_i, A)$.

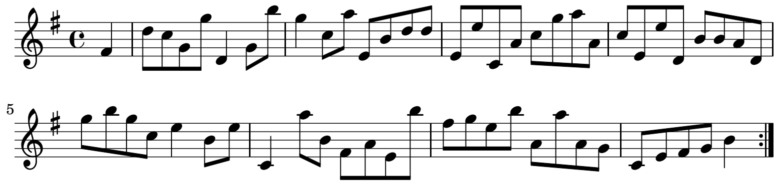
As an example, we tried to compose a new B section for the A section of Cooley's reel, the original correct version of which can be seen in fig. 1. Our new created B section can be seen in fig. 4.

While the resulting B section is musically far from ideal, it is notably better than the random starting B section. For example, the starting note is the same as that of the tune and the intervals between consecutive notes are, on average, smaller.

8 Further Work

At a broad level, all the work we have done could be improved by better feature selection. Given the complexities of music, 1- and 2-grams are far from ideal features. At the very least, we could store

Randomized notes used as a starting point for the optimization.



The new *B* section, converged upon in optimization.

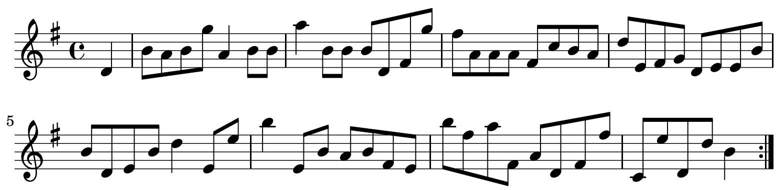


Figure 4: A new B section composed for Cooley's (see fig. 1), using its distance by the learned metric to the original A section.

counts of 3- or 4- (or more) grams, or subsets of these, thus encapsulating more of what a melody looks like on a larger scale. There are other obvious musical features that we have not looked into using, for example, time and key signatures. Even more musically-complex features may prove fruitful, for example, based on the notes in the melody at each point in time we could infer the chord progression. There is a lot left to explore in this regard.

As for improvements specific to our automated composition, one idea is to use our dataset to construct a model for the likelihood that a given sequence of pitches is musically significant. At the moment we are easily able to "converge" to a B section that, with respect to our learned metric, is actually closer to the given A section than the actual B section of the tune is. We produce a sequence of pitches that is similar to the A section but that, when viewed independently of this A section, still seems musically "unlikely." It is does not seem unreasonable, for example, that we could learn from our set of tunes that smaller intervals between notes are much more likely than large ones. One other complicating issue is that when performing PCA to reduce our feature vectors to only have at most 35 features (as is necessary for the metric learning implementation), we may lose essential musical information that is necessary for a tune to seem plausible to a human, as features that are unrelated musically may be represented by a single principal component in the transformed dataset. We might find improvements to the composition process by using a metric or likelihood estimation that is able to consider a larger number of features, or perhaps the untransformed original feature vectors themselves.

References

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