DISCRIMINATIVE NEURAL CLUSTERING FOR SPEAKER DIARISATION

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ABSTRACT
This paper proposes a novel method for supervised data clustering. The clustering procedure is modelled by a discriminative sequence-to-sequence neural network that learns from examples. The effectiveness of the Transformer-based Discriminative Neural Clustering (DNC) model is validated on a speaker diarisation task using the challenging AMI data set, where audio segments need to be clustered into an unknown number of speakers. The AMI corpus contains only 147 meetings as training examples for the DNC model, which is very limited for training an encoder-decoder neural network. Data scarcity is mitigated through three data augmentation schemes proposed in this paper, including Diaconis Augmentation, a novel technique proposed for discriminative embeddings trained using cosine similarities. Comparing between DNC and the commonly used spectral clustering algorithm for speaker diarisation shows that the DNC approach outperforms its unsupervised counterpart by 29.4% relative. Furthermore, DNC requires no explicit definition of a similarity measure between samples, which is a significant advantage considering that such a measure might be difficult to specify.

Index Terms— diarisation, supervised clustering, Transformer

1. INTRODUCTION
Clustering is the task of grouping data samples into multiple clusters such that a sample of a certain cluster is more similar to samples of the same cluster than to those of others. The performance of clustering algorithms is crucial for many applications. For speaker diarisation, the task to determine "who spoke when" [1, 2], audio segments are clustered according to speaker identities represented by high dimensional embeddings [3–6]. Commonly used clustering algorithms, such as agglomerative clustering [7–9], K-means clustering [10, 11] and spectral clustering [12–14], are mostly unsupervised and model-free, often leveraging pre-defined distance measures for the similarity between data samples.

The clustering task is challenging and inherently ambiguous when clusters are not clearly separated. Previously, various loss functions [6, 15, 16] and network architectures [14, 17] have been designed for embedding extraction such that the embeddings are better suited for the unsupervised clustering algorithms, including assumptions about the data distribution or the distance measures used. Therefore, it is desirable to use a parametric model that learns how to cluster directly from examples.

In Sec. 2, we propose the use of encoder-decoder models for supervised clustering – Discriminative Neural Clustering (DNC). As the supervised data for clustering is generally limited, we propose several data augmentation techniques in Sec. 3, which allow meaningful training of the DNC models. Before applying DNC to speaker clustering as the final stage of speaker diarisation, the experimental setup on the AMI meeting corpus is presented in Sec. 4. Section 5 demonstrates the performance of DNC comparing to a strong spectral clustering baseline. Analysis and conclusions are presented in Sec. 6 and 7.

2. DISCRIMINATIVE NEURAL CLUSTERING
Tasks that DNC can be applied to have the following structure. For input vectors $X = [x_1, \ldots, x_N]^T$, each vector $x_i$ belongs to the class $z_i$. At inference time each vector $x_i$ is to be assigned a label $y_i \in \mathbb{N}_1$, such that all vectors assigned the same label belong to the same class and vectors assigned different $y_i$ belong to different classes. This is a classical clustering task where the absolute label given to a cluster of vectors does not matter, but only the relative nature of the labels. For DNC to be applicable, multiple examples $(X, z_{1:N})$ have to exist. These are mapped to $(X, y_{1:N})$ by enforcing a specific ordering of the cluster labels $y_{1:N}$ as shown in the following examples.

| class label sequence $z_{1:N}$ | output label sequence $y_{1:N}$ |
|--------------------------------|----------------------------------|
| E A C A E E C                 | 1 2 3 2 1 1 3                   |
| A C A B B C D B D            | 1 2 1 3 3 2 4 3 4               |

Each $(X, y_{1:N})$ is a training example. In terms of diarisation, $X$ constitutes embedding vectors of each speech segment in a meeting and $z_{1:N}$ are the corresponding speaker labels. For a meeting with four speakers $y_i \in \{1, 2, 3, 4\}$.

2.1. Encoder-decoder Models for Supervised Clustering
Cluster boundaries are rarely clear. Without prior information, making clustering decisions (deciding how many clusters and cluster boundaries) is intrinsically ambiguous. Learning domain-specific knowledge contained within the examples can help to resolve ambiguitities. Cluster assignment $y_i$ of vector $x_i$ should be conditioned on the input sequence, to decide the cluster of $x_i$, and, to decide the specific value of $y_i$, on all assignments made for previous samples. Hence, we propose to model clustering with a discriminative model:

$$p(y_{1:N}|X) = \prod_{i=1}^{N} p(y_i|y_{0:i-1}, X),$$

where $y_0$ denotes a start-of-sequence token. For the model to be end-to-end trainable, we use a neural encoder-decoder model [18] (the N in DNC) which generally consists of two components

$$H = \text{ENCODER}(X);$$
$$y_i = \text{DECODER}(y_{0:i-1}, H),$$

where $H = [h_1, \ldots, h_N]^T$ is the encoded hidden representation of corresponding input vectors $X$. The encoder of the DNC transforms input features so that the hidden representation captures similarity.
information between samples. As in Eqn. (3), the decoder assigns the next label according to the labels assigned to previous samples.

2.2. Clustering Using Transformers

For both the Encoder and Decoder, various types of neural networks can be used including recurrent neural networks (RNNs) and attention mechanisms. As a particular type of DNC model, this paper uses the Transformer architecture of [19]. The choice is motivated by the Transformer’s handling of very long input sequences and the similarity of the dot-product attention with computing cosine similarities. The core operation of the Transformer is the multi-head attention (MHA). For a model with $H$ heads of $D$ dimensions each, scaled dot-product attention is defined by:

$$\text{ATTENTION} \Phi, \Psi = \text{softmax} \left( \frac{(\Phi \Psi)(\Psi \Psi)^T}{\sqrt{D}} \right) (\Psi \Psi),$$

(4)

$\Phi \in \mathbb{R}^{L \times D}$ is called queries. The matrices $\Psi \in \mathbb{R}^{L \times D}$ are called keys and values, which are identical. Queries and keys are multiplied by query and key projection matrices $\{W_q, W_k\} \in \mathbb{R}^{HD \times D}$. MHA has multiple heads, which are attention operations (Eqn. (4)) with distinct parameters. They are concatenated, then transformed by output matrix $W_o \in \mathbb{R}^{HD \times D}$ (Eqn. (6)).

$$\text{HEAD}_h(\tilde{X}) = \begin{cases} \text{ATTENTION}(\tilde{X}, \tilde{X}) & \text{for self attention} \\ \text{ATTENTION}(\tilde{X}, H) & \text{for source attention} \end{cases}$$

(5)

$$\text{MHA}(\tilde{X}) = \text{concat}(\text{HEAD}_1(\tilde{X}), \ldots, \text{HEAD}_H(\tilde{X}))W_o.$$  

(6)

Self-attention, the attention mechanism of an encoder block, operates purely on the input sequence $\tilde{X}$, thus $\Phi = \Psi = \tilde{X}$. Source attention is the attention mechanism in a decoder block. Keys and values are the hidden representation of the encoder ($\Psi = H$) and queries are the output of a self-attention layer operating on the history label sequence. Within each encoder or decoder block, residual connections [20] with layer normalisation [21] are used across layers. As the last step of the decoder, an output projection layer is used to obtain $p(y_i | y_{0:i-1}, X)$.

2.3. Comparison with Other Clustering Algorithms

The unsupervised clustering algorithm spectral clustering (SC) [12], in the form widely used for speaker clustering, often relies on pairwise cosine distances between all speaker embeddings. Speaker embeddings are often trained to maximise the cosine distances for different speakers while minimising the cosine distance for the same speaker. Transformers implicitly use the cosine distance through the dot-product attention mechanism of Eqn. (4). Compared to SC, DNC does not make any assumptions about cluster distributions.

Another supervised clustering approach that has been applied to speaker clustering is the unbounded interleaved-state RNN (UISRNN) [22]. It uses an RNN as a generative model where all speakers share the same set of RNN parameters but have different state sequences. Although the UIS-RNN is capable of handling an unlimited number of speakers, it assumes that the occurrence of speakers follows the same distance-dependent Chinese restaurant process [22] for all meeting scenarios. During the generative process of UISRNN, the next speaker embedding is modelled by a normal distribution with identity covariance matrix and the mean given by the RNN. The DNC model does not impose either of these assumptions. However, it does limit the maximum number of speakers.

Recent work on end-to-end models for diarisation [23, 24] combines neural networks with permutation invariant training (PIT) to directly produce cluster assignments from acoustic features. However, the method assumes independence of the output labels, even though they are strongly correlated in practice. The encoder-decoder structure of a DNC model conditions each output on the full output history. Moreover, the enforced ordering of $y_{1:N}$ ensures that PIT is not necessary, which would require additional forward passes.

3. DATA AUGMENTATION FOR DNC

DNC can be applied to tasks with limited training examples, such as diarisation. The issue of data sparsity is mitigated through three proposed data augmentation techniques, which can also be combined. The data augmentation techniques have two, possibly competing, objectives. The first is to generate as many training sequences $(X, y_{1:N})$ as possible. The second is to generate data that matches the true data distribution $p(X, y_{1:N})$ as closely as possible. Details of their application to diarisation are given in Sec. 5.

3.1. Random Sub-Sequences

The first data augmentation technique is to simply train on multiple sub-sequences $(X_{[a:e]}, y_{[a:e]})$ of the full sequence. It increases the number of examples and the same $y_i$ has different corresponding $y_i$ in different sub-sequences. Hence, the DNC model does not associate a particular input vector $x_i$ with a particular label $y_i \in \mathbb{N}_1$.

3.2. Randomisation of Input Vectors

The second technique, depicted in Fig. 1(a), modifies the input $X$ of each (sub-)sequence, but preserves the label sequence $y_{1:N}$. Hence, $y_{1:N} = [1 2 3 ...]$ is a sample of $p(y_{1:N})$. As many classes (options for $z_i$) as there are distinct $y_i$ in $y_{1:N}$ are chosen from the classes of the training set. These are mapped to the set of labels $\{1, 2, ..., N\}$ in one-to-one correspondence, automatically yielding $z_{1:N}$. For each $y_i$, a vector from the training set belonging to the class $z_i$ is chosen for $x_i$. In Sec. 5 two specific approaches to choosing classes for $z_i$ and corresponding vectors $x_i$ are given in the context of diarisation.

3.3. Diaconis Augmentation

The third technique, called Diaconis augmentation (Diacon-Aug), is applicable in scenarios where the vectors $x_i$ are $L_2$-normalised, forming clusters on the surface of a hypersphere. This is true of the embeddings used in this paper for diarisation. Diacon-Aug rotates the entire input sequence $X$ to a different region of the hypersphere. This synthesises entirely new training sequences $(X, y_{1:N})$ with previously unseen $x_i$. To do so, a random rotation matrix is sampled and every vector in $X$ is multiplied by it. An example of such rotation is depicted in Fig. 1(b), with the path of the rotation drawn. The algorithm for uniformly sampling high dimensional rotation matrices was developed by Diaconis et al. [25], leading to the name of our novel data augmentation algorithm.
4. DIARISATION PIPELINE & CLUSTERING SETUP

In this paper, DNC is applied to speaker clustering, the final stage of speaker diarisation. Embeddings for segments of audio are clustered into clusters that represent a single speaker. The diarisation pipeline, clustering baseline and DNC model setup are outlined below.

4.1. Data and Segmentation

The multiple distance microphone (MDM) data of the AMI meeting corpus [26] is used for all experiments, where the official train, dev and eval split is followed. The eight-channel audio data is first merged into a single stream using BeamformIt [27].

| #meetings | avg. duration | #speakers |
|-----------|---------------|-----------|
| train     | 147           | 37.9 min  | 155       |
| dev       | 18            | 32.3 min  | 21        |
| eval      | 16            | 34.0 min  | 16        |

Table 1: Details of AMI corpus partitions used for both speaker embedding extraction and the DNC model training.

To compare the performance of spectral clustering and DNC, perfect voice activity detection is assumed by using the manual segmentation of the original dataset and stripping silences at both ends of each utterance. Some short segments exist that are completely enclosed within longer segments. For speaker diarisation, such segments are unrepresentative of the output generated by common segmentation schemes operating on single-stream audio. Moreover, the standard NIST evaluation pipeline ignores overlapping speech. Hence, such enclosed segments are removed from the dataset.

4.2. Segment Embedding Extraction

Clustering is performed on the basis of segments, i.e., one embedding \( x_i \) per segment. A segment embedding is the average of speaker embeddings within the segment where the embeddings are \( L_2 \)-normalised before and after averaging. Frame level embeddings are based on the d-vector model in [14]. They are trained for speaker classification with the angular softmax (ASoftmax) loss [28] using HTK [29] and PyHTK [30]. The ASoftmax loss ensures cosine similarity to be the ideal distance measure between embeddings used in spectral clustering and facilitates the averaging method to obtain segment embeddings. The speaker embeddings are 32 dimensional.

Using ASoftmax loss combined with a linear activation function for the penultimate layer of the extractor, the normalised speaker embeddings, and in turn segment embeddings, should be approximately uniformly distributed on the unit-hypersphere. Based on this assumption, the mean and variance of individual dimensions of segment embeddings should be close to zero and \( \frac{1}{\sqrt{32}} \), respectively. Empirically, this assumption fits well for the mean and most dimensions for the variance. Variance normalisation for the DNC models is done by scaling these embeddings by \( \sqrt{32} \).

4.3. Clustering

4.3.1. Spectral Clustering

The baseline uses the refined spectral clustering algorithm proposed in [13], the input of which is the segment embeddings described in Sec. 4.2. Our implementation inherits from the one published by [13], but the distance measure used in the K-means algorithm is modified from Euclidean to cosine to align exactly with [13]. The number of clusters is set to be between two and four.

4.3.2. Discriminative Neural Clustering Model

The Transformer used as the DNC model contains 4 encoder layers and 4 decoder layers with dimension \( D = 256 \). The total number of parameters is 7.3 million. The number of heads for MHA is 4. The model architecture follows [19] and is implemented using ESPnet [31]. Given that the input-to-output alignment for DNC is one-to-one and monotonic (see Sec. 2.1), the source attention between encoder and decoder, represented as a square matrix, could be restricted to an identity matrix. For the following experiments, the source attention matrix is masked to be a tri-diagonal matrix, i.e., only the main diagonal and the first diagonals above and below are non-zero. We refer to this type of restricted source attention as monotonic local attention.

4.4. Evaluation

Diarisation systems are evaluated by the diarisation error rate (DER), i.e., the combined duration of missed speech, false alarm speech and speaker error over the duration of the audio. To evaluate the clustering algorithm, DER becomes speaker error rate (SER) when perfect segmentation is assumed. The NIST scoring script is used with a collar of 250ms and overlapping speech is excluded.

5. EXPERIMENTAL RESULTS

5.1. Data Augmentation

The use of random sub-sequences (sub-meetings) (Sec. 3.1) is applied to the training set for all experiments, in addition to other augmentation techniques. For the dev set (used as the validation set), this augmentation technique is applied exclusively. All augmentation techniques are compared for sub-meetings of length 50 in Table 2. Per original meeting, which dictates the label sequence \( y_{1:N} \), 5000 sub-meetings with 50 segments are generated and augmented using the techniques of Sec. 3. Full meetings of the eval set are split into sub-meetings with at most 50 segments.

| randomisation | w/o Diac-Aug | w/ Diac-Aug |
|--------------|--------------|-------------|
| none         | 20.19        | 15.25       |
| global       | 14.47        | 19.80       |
| meeting      | 23.03        | 13.57       |

Table 2: SERs for different data augmentation techniques for sub-meetings of length 50 segments.

For diarisation on the AMI corpus, two variants of the input vector randomisation in Sec. 3.2 are used. The first one, referred to as global, samples speakers (the classes in \( z_{1:N} \)) uniformly at random from the training set. Each vector \( x_i \) is then randomly chosen from all segment embeddings of the training set belonging to speaker \( z_i \). The second variant, called meeting randomisation, first samples a meeting of the training set. Its speakers are chosen to form \( z_{1:N} \) and vectors \( x_i \) are chosen only from those vectors of the sampled meeting that belong to speaker \( z_i \). This preserves correlations among embeddings of a meeting. For global and meeting randomisation, all segments in the training set longer than 2 seconds are split into as many segments of at least 1 second as possible. The splitting is only used to obtain additional segment embeddings, leaving the label sequences untouched.

This additional augmentation yields significant improvement.
The SER of a DNC model trained on unmodified data (none), is 20.19%. Using the global augmentation this is reduced to 14.47% SER, whilst meeting augmentation only achieves an SER of 23.03%. Neighbouring embeddings can be difficult to cluster due to overlapping speech. For short sub-meetings, meeting randomisation can move such neighbouring embeddings into separate sub-meetings. Hence, meeting might also not generate typical data, whilst providing far less augmentation than global.

The trend is different after applying Diac-Aug (2nd col. Table 2). Using none achieves an SER of 15.25%. The result for meeting is reduced to 13.57%. This shows that Diac-Aug generates fairly typical data. Sec. 4.2 showed that the assumptions are not perfect, which explains the performance drop of global. The number of speaker groups available from global (∼C_4^{156}) is larger than the number of sub-meetings. Thus, Diac-Aug does not increase the number of speaker groups seen by the DNC model when using global.

### 5.2. Curriculum Learning Scheduling

Training directly with entire meetings, using meeting and Diac-Aug, lead to a high SER. A curriculum learning (CL) [32, 33] approach, i.e. training in increasingly difficult stages, is used as learning long sequences is hard. First, sub-meetings with 50 segments are chosen to reduce the input space. Containing fewer speakers on average, such sub-meetings represent an easier task. Afterwards, the maximum length increases to 200, then to 500 and then to the full length (up to 1682 segments). The model is trained to convergence in all four stages. Each sub-meeting has a variable length between 50% and 100% of the maximum length in each of the last three stages. Meetings of the eval set are split into as few sub-meetings as possible, each not longer than the maximum length. A further CL strategy is to initially use stronger data augmentation followed by less data augmentation. This fits the CL framework as the augmentation technique that is removed for finetuning makes the training data easier.

For meeting lengths above 50, per original meeting, 10^4 sub-meetings are chosen and modified using the augmentation techniques. For maximum length 200, applying the two best-performing techniques of Sec. 5.1 results in an SER of 19.14% for global and 16.92% for meeting combined with Diac-Aug. The latter technique will be continued for the later stages of the CL. Moving to a maximum sub-meeting length of 500 results in an SER of 17.73% and for the full sequence length of 20.65%. These results for meeting with Diac-Aug are shown in Table 3 (col. DNC–data aug.).

Table 3 also shows the results of finetuning the DNC models (col. DNC–finetune). During finetuning, only Diac-Aug is used. Although the SER does not always improve, the SER on the dev set was reduced in all cases. This is why the finetuned models should be compared with SC. For all meeting lengths the DNC model outperforms SC. The finetuned DNC model for the full meeting length achieves an SER of 16.92%, which reduces SER over SC by 29.4% relative. The SER of a DNC model trained with meeting and Diac-Aug, but without CL, is only 34.48% after finetuning.

| (sub-)meeting length | DNC data aug. | finetune | SC |
|----------------------|--------------|----------|----|
| #segments            | duration     |          |    |
| 50                   | 2.8 mins     | 13.57    | 13.90 | 15.89 |
| 200                  | 9.7 mins     | 16.92    | 16.75 | 22.38 |
| 500                  | 20.9 mins    | 17.73    | 18.39 | 23.56 |
| all                  | 34.0 mins    | 20.65    | 16.92 | 23.95 |

Table 3: Comparison of DNC vs. SC at different CL stages. Finetuned DNC models are initialised from the corresponding models using full data augmentation.

### 6. ANALYSIS

Figure 2 visualises clustering results of a sub-meeting of the eval set using a 2D t-SNE [34] projection of the 32D segment embeddings. In Fig. 2(a), depicting the ground truth labels, there are no clear cluster boundaries. Spectral clustering (SC) is only able to pick out two speakers in Fig. 2(b), resulting in a high SER. The DNC model correctly recognises the existence of four speakers. Figure 2(c) and Fig. 2(d) show the comparison between the behaviour of SC (assuming the number of clusters is known) and the DNC model. The cluster boundaries are relatively clear for SC. However, the DNC approach has more complex boundaries and shows multiple points of cross over to other clusters, similar to Fig. 2(a). More importantly, the SC algorithm shows a higher degree of confusion when two clusters have significant overlap, e.g. it wrongly clusters many samples from speaker B to speaker A, whereas the DNC model splits these two confusing clusters better. In this case, DNC yields a much lower SER than the spectral clustering.

### 7. CONCLUSIONS

We have proposed Discriminative Neural Clustering (DNC), a novel supervised clustering approach. DNC models were trained using three essential, targeted data augmentation techniques and curriculum learning. DNC was shown to perform much better than spectral clustering on a speaker diarisation task. Given that the neural network used to extract d-vectors is differentiable, DNC can be extended to an end-to-end trainable model for speaker diarisation. Furthermore, instead of optimising the segment level cross-entropy, the final evaluation objective could be directly minimised. To perform online diarisation the Transformer-based DNC models can be modified to use forms of monotonic attention [35, 36].

![Fig. 2: Comparison of the clustering algorithms for a meeting of length 156 segments. 32D embeddings are projected using t-SNE.](image-url)
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