The Good, the Bad and the Noisy: Acoustic Features in Cross-Domain Argument Mining

Oscar Morris
ID: 2497790
AC40001 Honours Project
BSc (Hons) Computing Science
University of Dundee
Supervisor: Dr. R. Ruiz-Dolz
April 2025

Abstract

Recent advances in argument relation identification have begun to look beyond the domain in which they were trained such that these systems can robustly deal with the wide variety of domains they would see in a practical application. In many domains, the data stem from a dialogue (e.g. political debates), the additional paralinguistic features present in the audio data have, until recently, gone unexplored. Work exploring the addition of acoustic data has previously been hampered by a lack of available corpora. In this project, the largest multimodal argument relation identification dataset currently available is presented, along with a cross-domain dataset. These datasets are then used to evaluate nine different multimodal techniques in both an in-domain and a cross-domain environment. It was found that while the addition of acoustic features does not provide a significant improvement over text only solutions, the process used to combine the data from each sequence in the pair is vitally important to the performance of the model.

1 Introduction

Argument relation identification (ARI) is a subtask of argument mining (AM) involved with the detection and classification of the argumentative components contained within text and discussion [1]. AM generally can cover many different tasks, including argumentative sequence detection, argument component classification and ARI in a specific domain. All of these tasks (often when combined) have many different applications such as fake news [2] and fallacy detection [3] with uses across many fields including political science, military and corporate intelligence, and education. In all of these fields, it is important to be able to extract arguments and their relations accurately and with ease.

In many contexts (e.g. political debates or court proceedings) both the audio and textual data exist, where typically the text has been transcribed from the audio. Previously, most argument mining systems have focused completely on the textual data, often gained from a transcript of these discussions or debates. More recent research, however, has shown that the paralinguistic features available from other modalities of data (either images or audio) are able to improve the performance over text only solutions [4].

Multimodal models have shown the greatest level of improvement in argumentative sentence detection and argument segmentation [5]. However, they have only had varying degrees of success in ARI with Mancini *et al.* [6] finding the addition of acoustic features significantly increased performance while Mestre *et al.* [7] find no significant difference. Recent advances in multimodal models and their pre-training have now allowed the effective addition of acoustic features [8, 9], along with advances in other areas of natural language processing, more specifically, the advent of the transformer [10] and the recent boom of large language models (LLMs), including their use in text-based argument mining [11]. Due to their size, LLMs perform very well across a variety of domains and fields, but at great computational cost. Therefore, it is pertinent to understand how smaller models perform across a number of domains.

Traditionally, AM systems have been evaluated on the same domain that they were trained on [12, 13]. But given the recent uses of relatively task agnostic pre-training approaches and models such as BERT [14] and then the advent of LLMs has further increased the need for domain agnostic models. These advancements have also been applied to argument mining by evaluating models on datasets and domains with which they were not trained [15, 16]. This approach has not yet been evaluated on multimodal models generally nor text-audio models specifically, in any sub-task of argument mining, it is very possible that the addition of acoustic features will be helpful for the model to learn more intrinsic, less domain-specific features and therefore increase its ability to generalise beyond the domain in which it was trained. A likely reason that this has not been studied further is the relative lack of resources and available datasets designed for text-audio ARI. The only datasets currently available for the task are the M-Arg political debate dataset [7] with 7 hours of audio data, and the VivesDebate-Speech dataset [5] with 12 hours of audio data. Although they are the largest text-audio datasets of their type which are currently available, when comparing to the large text only datasets they are still relatively small. For example, M-Arg and Vivesdebate-Speech contain 6,527 and 7,810 nodes with one of the largest debate datasets, QT30 [17] containing almost 20,000. This difference in size means that there is still significant room for multimodal ARI datasets to grow and hints at a limitation surrounding the current approaches and models.

It is for this reason that the goals of this project are twofold:

(i) Extend two existing debate corpora with their audio data, allowing their use for all multimodal or audio only AM applications. The first of these is the large QT30 corpus [17] and the second is a smaller, but cross-domain corpus created from Moral Maze episodes [18].

(ii) The implementation and evaluation of different multimodal techniques and models in a cross-domain setting on the task of argument relation identification.

2 Background

2.1 Argumentation Theory

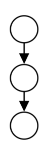
Argument and debate has been studied since the time of the ancient Greek philosophers and rhetoricians where argument theorists have sought to formalise discourse and discover some standard of proof for determining the ‘correctness’ of an argument. Over time, theories of arguments and discussions have evolved, notably when Hamblin [19] refashioned an argumentative discourse as a game, where one party makes moves offering premises that may be acceptable to the another party in the discourse who doubts the conclusion of the argument. When viewing a discourse as a game, it becomes possible to model discourse in such a way that it can be viewed through the lens of formal logic, and therefore computationally too.

In order to describe various dialogue, argument and illocutionary structures different models (annotation schemes) can be used, some annotation schemes focus on types of the text itself (such as speech act theory [20]) or on the types of relations between components (such as Rhetorical Structure Theory [21]). Inference Anchoring Theory (IAT) [22] is an annotation scheme constructed to benefit from insights across both types, whilst focusing specifically on argumentative discourse. This makes IAT a very useful tool to analyse arguments and their relations.

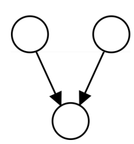
In IAT, the discourse is first segmented into Argumentative Discourse Units (ADUs). An ADU is any span of the discourse which has both propositional content and discrete argumentative function [23]. An IAT argument graph is typically composed of two main parts: the left-hand side and the right-hand side. The right-hand side is concerned with locutions and transitions between them. A locution is simply the text of the ADU as uttered, without reconstructing ellipses or resolving pronouns. Locutions also include the speaker and may even include a timestamp. Transitions connect locutions capturing a functional relationship between predecessor and successor locutions (i.e. a response or reply). The left-hand side of an argument graph is more concerned with the content of the ADU, rather than directly reflecting what was uttered. This consists of the propositions made, and the relations between those propositions. To create a proposition from an ADU, the content is reconstructed to be a coherent, lone-standing sentence. This means that any missing or implicit material has to be reconstructed, including anaphoric references (e.g. pronouns). Performing this reconstruction allows both a human annotator and a computational system to view some of the context surrounding the locution and therefore make a better judgement as to a proposition's relation to others.

IAT defines three different types of propositional relation: *inference*, *conflict* and *rephrase*. An inference relation (also termed RA) holds between two propositions when one (the premise) is used to provide a reason to accept the other (the conclusion). This may include annotation of the kind of support e.g. Modus Ponens or Argument from Expert Opinion. These subtypes of relation are often called *argument schemes* [24, 25]. There are also several different inference structures (images from [1]):

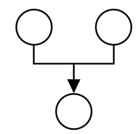
- **Serial arguments** occur when one proposition supports another, which in turn supports a third.



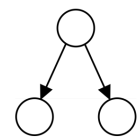
- **Convergent arguments** occur when multiple premises act independently to support the same conclusion.



- **Linked arguments** occur when multiple premises work together to support a conclusion.



- **Divergent arguments** occur when a single premise is used to support multiple conclusions.



A conflict relation (also termed CA) holds between two propositions when one is used to provide an incompatible alternative to another and can also be of a given kind (e.g. Conflict from Bias, Conflict from Propositional Negation). The following conflict structures are identified by IAT:

- **Rebutting conflict** occurs if one proposition is directly targeting another by indicating that the latter is not acceptable.
- **Undermining conflict** occurs if a conflict is targeting the premise of an argument, then it is undermining its conclusion.
- **Undercutting conflict** occurs if the conflict is targeting the inference relation between two propositions.

A rephrase relation (also termed MA) holds when one proposition rephrases, restates or reformulates another but with different propositional content (i.e. one proposition cannot simply repeat the other). There are many different kinds of rephrase, such as Specialisation, Generalisation, Instantiation etc. Generally, question answering will often involve a rephrase because the propositional content of the question is typically instantiated, resolved or refined by its answer. In contrast to inference, conflict and rephrase structures only have a single incoming an one outgoing edge.

The left and right-hand sides are connected by *illocutionary connections*. These illocutionary connections are based on illocutionary force as introduced by speech act theory [20]. The speech act $F(p)$ is the act which relates the locution and and the propositional content p through the illocutionary force F e.g. asserting p, requesting p, promising p etc. There are many diferent types of illocutionary connection, including: assertions, questions, challenges, concessions and (dis-)affirmations [26]. By modelling these relations it is possible to gain a better understanding of how something is said and its purpose within the discourse. In doing this, we create a graph (known as an *argument map*) which can then be stored computationally.

Several ways to store argumentative data have been created, for example Argument Markup Language (AML) [27], an XML-based language used to describe arguments in the Araucaria software. More recently, the Argument Interchange Format (AIF) [28] has been created to standardise the storage of IAT graphs.

AIF treats all relevant parts of the argument as nodes within a graph. These nodes can be put into two categories: *information nodes* (I-nodes) and *scheme nodes* (S-nodes). I-nodes represent the claims made in the discourse whereas S-nodes indicate the application of an argument scheme. Initially I-nodes only included the propositions made [28], but when Reed *et al.* [29] extended AIF to cater to dialogues, they added L-nodes as a subclass of I-nodes to represent locutions. For the purposes of this research, I-nodes and L-nodes are considered separate classes where I-nodes contain propositions and L-nodes contain locutions.

Since AIF data can be easily shared, it became the basis for a Worldwide Argument Web (WWAW) [30]. Since then, many corpora have been annotated using IAT and published on the AIFdb[1] [31] providing a very useful resource for argumentation research of many kinds.

2.2 Natural Language Processing

In recent years there have been several major advances in the field of natural language processing (NLP), most notably the introduction of the transformer architecture [10]. The transformer architecture, based on self-attention, allows the model to determine much longer range dependencies than previous approaches. In doing so, the model is able to learn from the context surrounding a word, even gaining insight from context 'far away' in the text.

Even before Vaswani *et al.* introduced the transformer architecture supervised and semi-supervised pre-training approaches were already being explored, and proven to be a very useful tool for improving the performance of language models [32, 33]. When the transformer was introduced these pre-training techniques were adapted for use in transformers creating models which are able to be fine-tuned with relatively minimal effort and compute to allow high performance on a wide variety of tasks [14, 34]. The pre-training approaches introduced by BERT and RoBERTa use a combination of masked language modelling (where the model is trained to predict the token hidden under a `[mask]` token) and next sentence prediction. The models are then trained using this approach on large datasets (the dataset used to pre-train RoBERTa totals over 160GB of uncompressed text).

Transformer models have recently become much more well-known due to the introduction of Large Language Models (LLMs) such as GPT-4 [35] and LLaMA [36]. LLMs have proven very useful across NLP due to their ability to achieve high performance on many tasks without the need for fine-tuning, this can, however, include few-shot techniques to allow them to 'learn' at inference time [37, 38].

A similar progression can be seen in the development of audio models. Pre-training was notably introduced into speech recognition with wav2vec [8], where the model is trained to predict future samples from a given signal. The wav2vec model has two main stages, first raw audio samples are fed into a convolutional network which performs a similar role to the tokenisation seen in text-based language models by using a sliding window approach to downsample the audio data. These encodings are then fed into a second convolutional network to create a final encoding for the sequence.

Transformer models were introduced into the architecture of audio models with wav2vec2 [39] and HuBERT [40], where the second convolutional model is replaced with a transformer in order to better learn dependencies across the entire sequence. These models are then pre-

[1] https://www.aifdb.org/

trained on significant amounts of audio data (960 hours in the case of wav2vec2) in order to then be fine-tuned on a downstream task. It is also possible to combine text and audio in order to gain insights from both modalities.

Combining modalities (such as text and audio) has also proven to be a useful tool across several tasks, including medical imaging [41, 42] and natural language processing [43, 44], including argument mining [6, 7]. Generally fusion techniques can be split into two categories: early and late. Early fusion techniques combine representations of each modality before being used as input to an encoder, with the primary benefit that only a single encoder is used. Late fusion techniques use a separate encoder for each modality, and the encodings are then fused to provide a crossmodal representation of the input.

In early fusion the input representations are transformed into a common information space, often using vectorisation techniques dependent on the modality. Late fusion techiques allow for the encodings of each modality to be combined in several different ways, often either simple operations (such as concatenation or an element-wise product) but a cross-modal attention module can also be used to combine the modalities [45, 46]. The fusion techniques used in this project are explained in detail in Section 4.

2.3 Argument Mining

Various NLP techniques have been beneficial to AM, from statistical methods to the more recent neural networks, in particular the transformer architecture [15]. Before discussing the automation of AM, it is useful to understand how argument analysis is conducted manually. Manual argument analysis considers the following steps:

- **Text Segmentation** involves the splitting of the original text/discourse into the pieces that will form the resulting argument structure. These pieces are often termed Elementary Discourse Units (EDUs).
- **Argument / Non-Argument Classification** is the task of determining which of the segments found in the text segmentation step are relevant to the argument. For most manual analysis, this step is performed in conjunction with text segmentation i.e. the analyst doesn't segment parts of the text which are not relevant to the argument.
- **Simple Structure** is the identification of relations between the arguments (e.g. inference, conflict and rephrase) and their structures (e.g. convergent, serial etc.).
- **Refined Structure** refers to the identification of argumentation schemes (e.g. Argument from Expert Opinion, Conflict From Bias etc.).

When the argument analysis process is automated, the stages are very similar to those in the manual process. Lawrence and Reed [1] define the steps as follows, increasing in computational complexity:

- **Identifying Argument Components** combines the stages of text segmentation and argument / non-argument classification in the manual process.
- **Identifying Clausal Properties** involves the identification of both intrinsic clausal properties (e.g. is X evidence?, is X reported speech?) of the ADU and the contextual properties (e.g. is X a premise?, is X a conclusion?).
- **Identifying Relational Properties** relates to the identification of *general relations* between ADUs (e.g. is X a premise for Y?, is X in conflict with Y?) and the identification of argument schemes.

Generally these stages of AM are not directly used in the literature, but instead a set of AM sub-tasks which map onto each of these stages, these tasks are defined by Mancini et *al.* [6] as follows:

- **Argumentative Sentence Detection (ASD)** is the task of classifying a sequence as containing an argument, or not. ASD can be extended to include the task of claim detection, where a sequence is classified as containing a claim or not containing a claim.
- **Argument Component Classification (ACC)** is the task of determining whether an argumentative sentence x contains one or more argumentative components e.g. a claim or premise. This is loosely analogous to the identification of clausal properties as defined by Lawrence and Reed.
- **Argumentative Relation Identification (ARI)** is the task of identifying the relation between a pair of sentences where given a pair (x_i, x_j) the task is to

identify the argumentative relation $x_i \to x_j$ across some relation model.

There are varying relation models for ARI, the most commonly used is simply classifying the pair as one of support (a combination of inference and rephrase), attack (conflict) or unrelated. For the purposes of this project this is termed 3-class ARI. ARI can also be conducted using all relations described in IAT (inference, rephrase and conflict), as well as unrelated nodes. For the purpose of this project this is termed 4-class ARI. Some literature makes a distinction between Argument Relation Identification and Argument Relation Classification, where the latter does not involve unrelated pairs (i.e. given that the pair (x_i, x_j) is related, what is the type of relation?), however this distinction is by no means universal among AM literature [16].

Much of the AM literature only evaluates their systems in the same domain (dataset) as it was trained on [1, 11–13, 47, 48]. Recently, however, more research has been conducted into how these models perform across different domains [15, 49, 50], this generally involves training the model on one domain and then evaluating its performance across several others. A good example of this is the ARIES benchmark [16], which provides results for various different approaches to the ARI task across popular ARI datasets. Another notable contribution is Ruiz-Dolz *et al.* (2021) [15] which compares the cross-domain performance of the most popular pre-trained transformer models (e.g. BERT [14] and RoBERTa [34]) showing that the RoBERTa models tend to perform better both in-domain and cross-domain. In order to perform a cross-domain evaluation, it is useful to understand how the data can be constructed and what influence that has.

Considering the sampling of nodes, if the nodes are related it is fairly trivial, however, If all possible examples of unrelated samples are used it constitutes an overwhelming proportion of the dataset (98-100%) which would be detrimental to model performance in the real world. Techniques to solve this problem were devised by Ruiz-Dolz *et al.* [51] who propose the following methods:

- **Undersampling** creates a more balanced class distribution by randomly choosing unrelated propositions from the set of all possible combinations.
- **Long Context Sampling** where unrelated propositions are chosen such that they are ‘far apart’ in the discourse. Ruiz-Dolz *et al.* define this as being from different argument maps.
- **Short Context Sampling** where unrelated propositons are chosen such that they are ‘close together’ in the discourse. Ruiz-Dolz *et al.* define this as being from the same argumet map.
- **Semantic Similarity Sampling** where unrelated propositions are chosen such that they are semantically similar.

They show that Short Context Sampling is the most challenging method when looking in-domain, however, the model is better able to generalise across different domains than the other methods and is a more realistic task.

Next, the applicability of these techniques is extended to multiple modalities. AM has been performed using both Vision-Language systems [52–54] and perhaps the more obvious Audio-Language systems [4–6]. Making use of acoustic features has been shown to improve performance across both ASD and ARI tasks [5, 7] but there has not been any research into the applicability of Audio-Language systems in cross-domain contexts.

Mancini *et al.* [6] created a comprehensive toolkit for argument mining research. They include both datasets and models that can be used for the creation and evaluation of audio-language argument mining systems, across different tasks, including ASD, ACC and ARI. Therefore, MAMKit provides a very useful benchmark for the development of audio-language AM techniques.

3 Datasets

All argument data used in this project are available as corpora on AIFdb[2]. Using consistently annotated Argument Interchange Format (AIF) data allows many different datasets to be used and tested. The AIF Format [28] allows the annotation of argument data across all AM tasks, providing a platform for many different kinds of research.

[2]https://corpora.aifdb.org/

Throughout the project two primary corpora have been considered: QT30 [17], a corpus consisting of 30 AIF annotated Question Time episodes, and a corpus of 9 AIF annotated Moral Maze episodes available on AIFdb [18].

3.1 Preprocessing

3.1.1 Argument Data

In order to use AIF data efficiently for ARI, it is useful to perform some preprocessing. This process produces a graph, where each node contains a locution, its related proposition, and the proposition's AIF identifier. This identifier corresponds to the audio data, allowing it to be easily loaded when required. Each edge in this graph corresponds to a relation between the propositions, one of RA (inference), MA (rephrase) or CA (conflict).

Figure 1 shows an example sub-graph from the larger argument graph. Each node is truncated for brevity and only shows the node's ID, and the proposition. The major downside of processing the data in this way is simply that much of the nuance encoded within AIF is lost. This is primarily the advanced structures (e.g. linked arguments, undercutting conflict etc.) but also the transitions and illocutionary connections. In the context of this project this is not an issue but is worth remembering when examining the data.

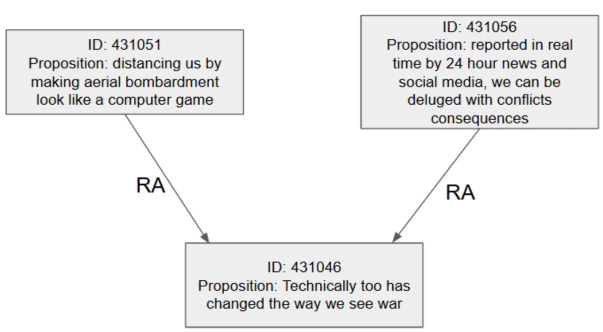


Figure 1: Example sub-graph.

An example of the JSON structure used to store the argument data is shown in Listing 1. It is also worth understanding the link between the locution and the proposition, of which those in Listing 1 are good examples. The locution is exactly what is said, and the speaker is given (in this case Matthew Taylor), whereas the proposition can be thought of as adding a bit more context from the surrounding dialogue. This primarily includes pronoun resolution as seen in the first word "she" in the locution vs. "Nancy Sherman" in the proposition.

Listing 1 Example JSON object corresponding to a Node.

```
{
    "id": 433407,
    "locution": "Matthew Taylor : she answered questions about norms and structures by talking about beliefs and campaigns and I think beliefs are different to norms and I think campaigns are different to social structures",
    "proposition": "Nancy Sherman answered questions about norms and structures by talking about beliefs and campaigns and beliefs are different to norms and campaigns are different to social structures",
    "relations": [
        {
            "type": "CA",
            "to_node_id": 433393
        },
        {
            "type": "RA",
            "to_node_id": 433416
        }
    ],
}
```

An array of these JSON objects can then be used to create the node pairs required for the training and evaluation of the model.

3.1.2 Forced Alignment

Design The audio data first had to be downsampled from 44.1kHz to the 16kHz which is best accepted by the Wav2Vec2 transformer [39] among many others. This can easily be achieved using FFmpeg[3]. In the case of QT30, first audio had to be extracted from the video, and collapsed into a mono track before it could be downsampled, this was also easily achieved with FFmpeg.

Next, start and end times for each locution in the argument graph need to be found, to allow the audio to be split per-locution (and therefore per node). This can be achieved using Connectionist Temporal Classification (CTC) [55] as exposed by PyTorch's forced alignment api[4]. CTC allows a model to classify the data in a certain timestep into one of several categories (in this case each letter) considering the data in surrounding timesteps. This then provides the probability distribution across a set of tokens, for each timestep (known as a frame). For a forced alignment task, these tokens are typically each letter of the alphabet and a blank token. The blank token is used for frames which cannot be classified as any other token (e.g. silence).

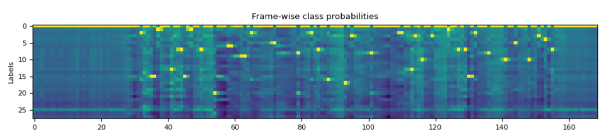


Figure 2: Example framewise probabilities.

Figure 2 (taken from the PyTorch tutorial on the subject[5]) shows an example of the framewise probability distribution across each token, token 0 here is the blank token. This distribution provides the probability (or confidence) of any particular token appearing in any given frame. Taking simply the most probable tokens provides something that looks like the following: `- i - - h h a - - - d -`, where – represents the blank token. That sequence describes the words 'I had', so it can be seen that the duplicates need to be removed, along with the blank tokens. This is the process that would be undertaken for Automated Speech Recognition.

When looking at forced alignment, however, the process is a bit different since we already have a transcript. For forced alignment the goal is to find the most probable route through the framewise probability matrix which matches the transcript. To do this a so-called trellis matrix can be generated. Here it is useful to envision two 'pointers', one of which represents the current frame in the audio and the other represents the current position in the transcript. Then for every transition between frames, consider the probability that the position in the transcript remains the same vs. the probability that it moves forward one character.

We are then looking for the path across the most likely transitions, $k_{(t+1,j+1)}$, where j is the current location in the transcript, and t is the current timeframe. The trellis can then be defined as in Equation 1.

$$k_{t+1,j+1} = \max\Big(k_{(t,j)}p(t+1, c_{j+1}), \quad k_{(t,j+1)}p(t+1, repeat)\Big) \tag{1}$$

Where k is the trellis matrix and $p(t, c_j)$ is the probability of any token c_j appearing in frame t, effectively referencing the framewise probability matrix, and $repeat$ represents the blank token.

Once the trellis matrix is generated, an example of which is shown in Figure 3[6] where the yellow high-probability path is visually obvious, it can be traversed using a backtracking algorithm, starting from the last token in the transcript and following either $(c_j \to c_j)$ or $(c_j \to c_{j-1})$ transitions, based on their probability, until reaching the beginning of the transcript.

At this point, we have start and end frame-numbers for each token, and based on the probabilities the model has traversed, a 'confidence' score can be calculated based on the mean of the probabilities traversed, this group of three values is known as a span (in this case a token span). The token spans can be generated by using the

[3]https://ffmpeg.org/
[4]https://pytorch.org/audio/
[5]https://pytorch.org/audio/main/tutorials/ctc_forced_alignment_api_tutorial.html
[6]https://pytorch.org/audio/main/tutorials/forced_alignment_tutorial.html

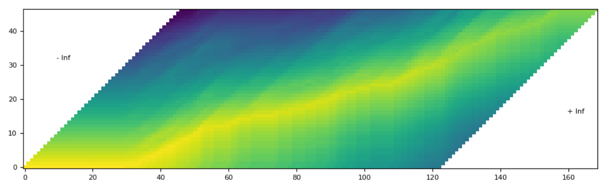


Figure 3: Example trellis matrix where yellow shows a high probability.

PyTorch forced alignment API, allowing the algorithm to be easily implemented and used. Finally, the token spans can be combined into word spans based on word boundaries in the transcript. This provides start and end frame numbers for each word, along with a confidence score. The same process can be conducted later to find a locution-level span with a confidence score. The frame numbers can then be easily converted back into times in the waveform and then split into the required segment.

Implementation Initially the forced alignment of the argumentative discourse was achieved by aligning each word in the complete transcript of the episode, producing start and end times for each word. A search can then be performed through these data to find the required locution. While this technique initially produced promising results, it was not robust enough to allow for errors in the transcripts or the crosstalk common in debates. This problem can be seen in the fact that the trellis matrix only allows for a single token to appear in each timeframe, which is trivially not applicable to the real world in an argumentative context where a lot of crosstalk (multiple speakers talking over each other) exists.

To solve this problem, the PyTorch forced alignment API is able to take wildcard tokens as input, therefore, each locution can be searched for individually. To achieve this, the partial transcript used as input to the forced aligner took the following form: $\star$ `{locution}` $\star$.

Using this system allows the forced aligner to work well through crosstalk (since each locution's alignments are searched for independently of all others), and qualitatively seems to be more resilient to errors. Error resilience is helped since errors are less common in the locution texts as opposed to the transcripts. Using this system also allowed for confidence scores to be collected for analysis. In Section 3.1.3 general analysis across all corpora is performed, with corpus specific analysis in the relevant section.

3.1.3 Audio Data

Figure 4 shows the distribution of confidence scores across both the QT30 corpus and all Moral Maze corpora. This distribution shows that the system can relatively confidently align the majority of locutions, with only approximately 8% of locutions with a confidence score less than 0.50.

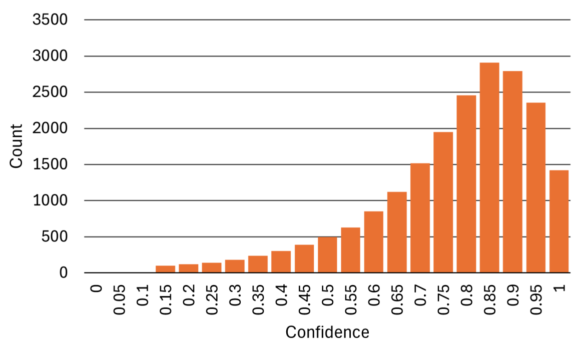


Figure 4: Confidence distribution across all corpora.

In order to further analyse the performance of this system, locutions were selected at random and qualitatively analysed. Throughout this process, all locutions appeared correct, however, it was very challenging to manually determine the accuracy of the system on locutions with confidence scores < 0.2 due to high amounts of crosstalk or other acoustic artefacts. This shows that this method of aligning locutions with their corresponding audio is accurate for the purposes of this project, as long as the confidence scores are taken into account. However, these confidence scores should not be mistaken for a 'probability of being correct'.

The distribution of lengths for each audio clip was also analysed in order to ensure the models are being provided with enough data. The primary statistics are shown in Table 1. These data shows that the majority of locutions are shorter than 8 seconds (approximately

120,000 samples at the sampling rate of 16kHz). In total, across both corpora, there is over 24 hours of argumentative audio, out of over 36 hours of total audio processed. The relevant data for the specific corpora are detailed in the relevant section.

Table 1: Audio data for locutions across all corpora.

Quantity	Length (s)	No. of Samples
Mean	3.9	62,000
75th Percentile	5.1	81,000
90th Percentile	7.7	120,000
Maximum	31	490,000

Next, a comparison can be made between the sizes of the datasets presented here (QT30-MM and Moral Maze) when compared to previous work in ARI and other AM subtasks. Table 2 compares the M-Arg [7], VivesDebate-Speech [5], UKDebates [56], MM-USED [4] and MM-USED-fallacy [57]. As far as could be ascertained, QT30-MM is by far the biggest multimodal ARI dataset created to date with 20 hours of argumentative audio and although the Moral Maze corpus only contains 5 hours of argumentative audio, it is the only cross-domain corpus. It should be noted, however, that the MM-USED and MM-USED-fallacy are larger argument mining datasets but only contain annotations for ACC or fallacy detection.

Table 2: Comparison between different multimodal argument mining datasets. Lengths are in hours. *dataset lengths were not reported by initial authors so are derived from downloaded audio data.

Dataset	Task	Length
M-Arg	ARI	7
VivesDebate-Speech	ARI, ASD	12
UKDebates	Claim Detection	2
MM-USED	ACC	43*
MM-USED-fallacy	Fallacy Detection	37*
QT30-MM	ARI	20
Moral Maze	ARI	5

3.1.4 ADU Pair Creation

Finally, a set of node pairs and their relations can be generated in order to train a neural network. For related nodes this can be done trivially in that for each relation, the corresponding pair of nodes can be added to the set. When sampling unrelated nodes, however, things are more complex.

It has also been shown that how unrelated node pairs are sampled is very relevant to the model's performance [51]. For this reason, it is also useful to provide a comparison between the different methods in a multimodal context. Since a short context is defined as being within an episode, the sampling strategies are only relevant for QT30, all Moral Maze episodes are simply undersampled. The following methods are compared:

- **Undersampling (US)** is the simplest method. The set of all possible pairs is created and then randomly undersampled to the number of inference/support relations.
- **Long Context Sampling (LCS)** samples unrelated nodes such that each node comes from a different episode with the result that they are 'far apart' in the discourse, this often takes the form of a different topic and such the task is slightly easier than the other methods. This list can then be randomly undersampled to the number of inference/support relations.
- **Short Context Sampling (SCS)** samples unrelated such that each node comes from the same episode so they are 'close together' in the discourse meaning that they often involve the same topic with the result that the task is slightly harder than other methods. This set is then randomly undersampled to the number of inference/support relations.

3.2 QT30

The QT30 argument corpus [17] contains transcripts and argument annotations for 30 episodes of the BBC's Question Time, a series of televised topical debates across the United Kingdom. All episodes aired in 2020 and 2021. The corpus is split into 30 subcorpora, each spanning a single episode. This creates a large corpus with almost 20k locutions. What follows is an analysis of the corpus and how audio data were added.

Table 3 shows the distribution of each type of relation across QT30. Inference and Rephrase relations make up a total of 91.5% of the dataset, with Conflict relations being significantly less common, only making up 8.5% of the dataset. It is obvious that this is an unbalanced dataset, which will have to be considered during training.

Table 3: Distribution of propositional relations in QT30.

Relation Type	Count	Proportion (%)
Inference	5,761	51.4%
Conflict	947	8.5%
Rephrase	4,496	40.1%
Total	11,204	100%

Figure 5 shows a box plot of the mean confidence values across each episode. This plot shows two outliers corresponding to the 22July2021 episode (with mean confidence 0.44) and the 30September2021 episode (with mean confidence 0.24). Manually analysing samples in these episodes indicates a high error rate in the alignment of locutions. Because of this high error rate, it was decided to exclude these episodes from the corpus used for training. The rest of the episodes from QT30 will form its multimodal subcorpus (QT30-MM) where QT30-MM has a mean confidence score of 0.75 with a standard deviation of 0.17.

As can be seen in Figure 6 the distribution of confidence scores closely matches that shown in Figure 4. This still indicates that the audio alignments are calculated with high accuracy.

Table 4 shows the distribution of relations after sampling unrelated nodes, this process increases the dataset size to a total of almost 17k samples. When comparing QT30 to QT30-MM the total number of relations only drops from 11,204 in QT30 to 11,156 in QT30-MM (only losing 48 relations), however, the quality of audio alignment does increase.

The audio data contained within the dataset can also be analysed as shown in Table 5. Generally the values are very similar to those shown in Table 1. The QT30-MM dataset contains almost 20 hours of argumentative audio

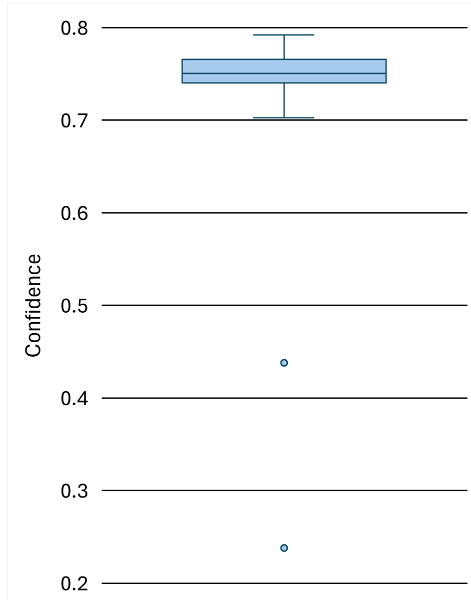


Figure 5: Box plot of episodic confidence values across QT30.

taken from approximately 29.5 hours of total audio. This makes the QT30-MM corpus the largest multimodal ARI dataset currently available.

3.3 Moral Maze

Similar to Question Time, the BBC's Moral Maze is a series of radio broadcast debates, with each episode focusing on a certain topic. Several episodes of the Moral Maze have been annotated with IAT and AIF and also made available on AIFdb. Of these episodes, eight were chosen from different fields. It is therefore these eight episodes, released from 2012 to 2019, which this project considers. Each episode focuses on a very different domain which allows for a robust, cross-domain analysis of any models trained on another corpus (e.g. QT30). The Moral Maze corpus contains data from eight different episodes: Banking (B), Empire (E), Money (M), Problem (P), Syria (S), Green Belt (G), Hypocrisy (H) and Welfare (W). Each episode consists of a debate focusing on a different topic, and hence has a different distribution of classes.

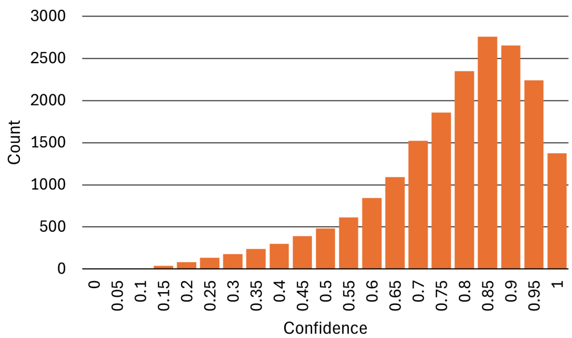


Figure 6: Confidence distribution across QT30-MM.

Table 4: Distribution of propositional relations after sampling non-related nodes.

Relation Type	Count	Proportion (%)
None	5,470	34%
Inference	5,470	34%
Conflict	937	6%
Rephrase	4,479	27%
Total	16,896	100%

Table 6 shows the distribution of propositional relations across the Moral Maze corpus, after unrelated pairs have been sampled. Comparing the corpus to QT30, a significantly lower proportion of the corpus is made up of Rephrase relations. It is possible that the differing formats of the debates has an impact here.

Figure 7 shows a box plot of the mean confidence scores for each subcorpus of Moral Maze. Generally the results match what is expected and are similar to those in QT30 although there are no outliers and therefore no episodes were omitted.

In Figure 8 the distribution of audio alignment confidence scores across all Moral Maze episodes can be seen. This follows the expected pattern as shown in Figures 4 and 6.

Table 7 shows the statistics for the audio part of the combined Moral Maze corpus. Generally the locutions seem to be a bit longer in the Moral Maze when compared to QT30. The Moral Maze combined corpus contains almost 5 hours of argumentative audio taken from approximately 6.5 hours of total audio.

Table 5: Audio data for locutions across QT30-MM.

Quantity	Length (s)	No. of Samples
Mean	3.8	60,000
75th Percentile	5.0	79,000
90th Percentile	7.5	120,000
Maximum	30	470,000

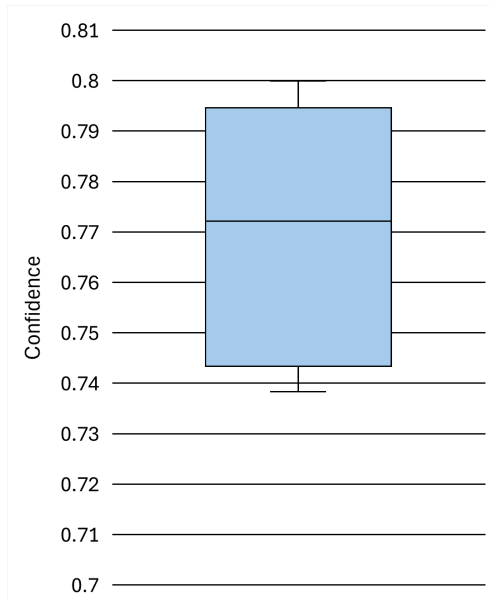


Figure 7: Per-subcorpus mean of confidence scores for each Moral Maze episode.

4 Models

This section descries the model architectures that are evaluated in this project. Since the models will be aimed at a sequence pair classification task, there is a distinction between when the data from each sequence is combined (which can be termed sequence fusion) and when the data from each modality is combined (which can be termed multimodal fusion). The following subsections define the different approaches evaluated for each

Table 6: Distribution of propositional relations across the Moral Maze corpus.

Subcorpus \Relation Type	None	Inference	Conflict	Rephrase	Total
B	132 (45%)	132 (45%)	24 (8%)	3 (1%)	291
E	151 (41%)	151 (41%)	39 (11%)	25 (7%)	366
M	255 (43%)	255 (43%)	29 (5%)	58 (10%)	597
P	236 (42%)	236 (42%)	40 (7%)	45 (8%)	557
S	181 (42%)	181 (42%)	63 (14%)	10 (2%)	435
G	301 (41%)	301 (41%)	46 (6%)	93 (13%)	741
H	207 (43%)	207 (43%)	23 (5%)	43 (9%)	480
W	211 (40%)	211 (40%)	59 (11%)	43 (8%)	524
Total	1,674 (42%)	1,674 (42%)	323 (8%)	320 (8%)	3,991

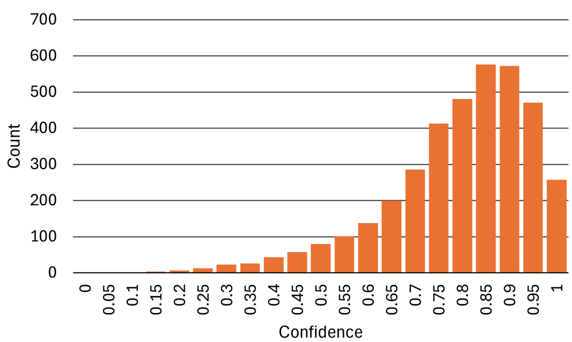


Figure 8: Confidence distribution across all Moral Maze subcorpora.

of these stages.

In previous work it has been shown that the RoBERTa models perform better than other pretrained transformers on the task of ARI [15]. To encode the text data, the RoBERTa-base model is used, with 12 encoder layers, each with 12 attention heads and a hidden size of 768, resulting in 110M total parameters[7]. Wav2Vec 2.0 is also used in many audio processing tasks [3, 6] and therefore is used to encode the audio data. To ensure both models output the same hidden size, the wav2vec2-base model is used with 95M total parameters[8]. The wav2vec2 model used is fine-tuned on 960 hours of librispeech for automatic speech recognition. Once the data have been en-

[7]https://huggingface.co/FacebookAI/roberta-base
[8]https://huggingface.co/facebook/wav2vec2-base-960h

Table 7: Audio data for locutions across Moral Maze.

Quantity	Length (s)	No. of Samples
Mean	4.4	70,000
75th Percentile	5.8	94,000
90th Percentile	9.0	140,000
Maximum	31	490,000

coded, it can be fed into the classification head to output a final prediction.

The classification head used for most models is a simple linear projection from the hidden vector down to the required number of classes. The best performing model on ARI as proposed in MAMKit [6] (MM-RoBERTa) is also evaluated. Their model uses the fusion architecture described in Figure 10 but with a 3 layer Multilayer Perceptron (MLP) model as the classification head. They also only train the classification head, without training the text or audio encoders.

4.1 Sequence Fusion

In most text-processing approaches the data from each sequence is combined at the text level using special tokens defined in the encoder's tokeniser [16, 47, 48]. For this project, this approach is termed early sequence fusion. To achieve this, the input sequences can be delimited by a separator token, and the entire sequence wrapped in the start of sequence (SOS) and end of sequence (EOS) tokens. An example using the RoBERTa tokeniser takes the following form:

```
<s> [sequence 1] </s>
[sequence 2] </s>
```

Here the <s> token corresponds to the SOS, and </s> does the job of both the separator token and the EOS token.

Next the audio data can be considered. As far as was found, there is no existing literature on how early sequence fusion could function for audio models. Therefore, it was decided to delineate each audio sequence by a certain amount of silence. The exact amount of silence could be adjusted as a training hyperparameter and was eventually set to 5 seconds.

Figure 9 shows an example of a model architecture using this late fusion technique, text related steps are shown in purple and audio related steps are shown in green. RoBERTa and Wav2Vec2 are simply used as examples and could be substituted for other models.

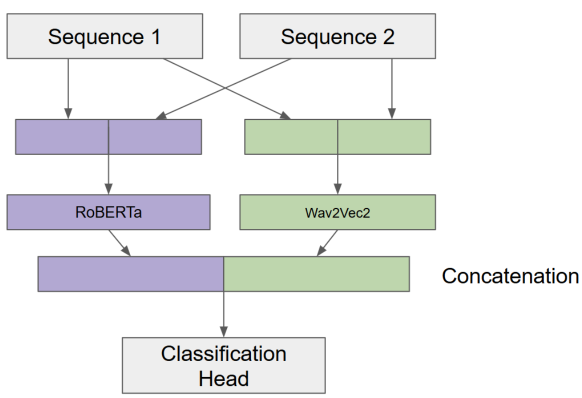


Figure 9: Model diagram with early sequence and late multimodal fusion. Purple denotes textual data and green denotes acoustic data.

Mestre *et al.* [7] and Mancini *et al.* [6] approach the problem differently. They first put each sequence through the text encoder independently, before fusing the outputs and feeding the combined encodings into the classification head. While concatenation is the only fusion method examined for this sequence fusion technique, others (such as an element-wise product or cross-attention) could be used. This approach extends much more easily to the audio modality, since the audio encodings can be combined in the same way as the text encodings. This approach to fusing the data in each sequence can be termed late sequence fusion. Figure 10 shows an example of a model architecture using late sequence fusion, text processing steps and data are shown in purple and audio-related steps are shown in green.

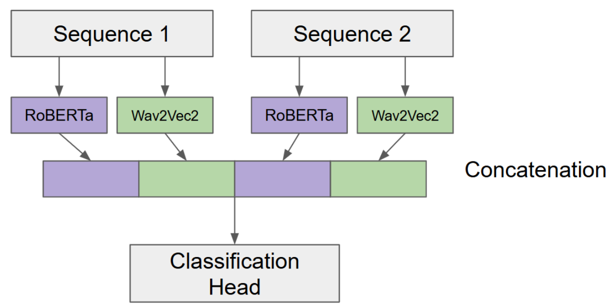


Figure 10: Model diagram with late concatenation sequence and multimodal fusion. Purple denotes textual data and green denotes acoustic data.

4.2 Multimodal Fusion

Multimodal fusion decribes the method by which the text and audio data are combined. As detailed in Section 2.2, fusion techniques can be split into two major categories: early and late fusion. This project only evaluates late fusion techniques due to their ease of development and the applicability of pre-trained models. The following techniques are evaluated:

- **Concatenation** where the pooled encodings for each modality are simply concatenated before being fed into the classification head.
- **Elementwise-product** (otherwise known as a Hadamard product) takes the product of each element in the pooled encodings for each modality.
- **Crossmodal Attention** (CA) is similar to the self-attention mechanism found in transformers, however, the queries are taken from a different modality when compared to the keys and values. To compute crossmodal attention features, the query and key matrices are multiplied and then put through a softmax. This is then multiplied with the value matrix and the result can then be pooled using an arith-

metic mean. For the purposes of this project, the CA module is labelled based on the modality from which the query matrix is derived (e.g. a `CA_Text` module derives the query matrix from the text encodings and the key and value matrices from the audio encodings). This is shown in Figure 11.

Listing 2 shows how a crossmodal attention mechanism can be implemented into a PyTorch module. The code is contained within the forward method of a PyTorch module, where `self.query_proj`, `self.key_proj` and `self.value_proj` are the linear projections for the queries, keys and values respectively. `torch.bmm` refers to a matrix multiplication and `F.softmax` is a mathematical function to ensure all values (across the requested dimension) lie in the range $[0, 1]$ and sum to 1, the softmax function for a vector $\mathbf{x}$ is given in Equation 2.

$$\text{Softmax}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)} \tag{2}$$

Listing 2 PyTorch forward method for a crossmodal attention mechanism.

```python
# project query features
queries = self.query_proj(query_modality)

# project kv features
keys = self.key_proj(kv_modality)
values = self.value_proj(kv_modality)

# compute attention scores
attn_scores = torch.bmm(queries, keys.transpose(1, 2))
attn_probs = F.softmax(attn_scores, dim=-1)

# compute and return cross modal features
return torch.bmm(attn_probs, values)
```

5 Results

5.1 Experimental Setup

To provide a comparable set of results, all experiments were run using the same hyperparameters. Each model was trained on a single Nvidia RTX 4070 Super for 15 epochs with a batch size of 32 using a weighted cross-entropy loss and the AdamW optimiser [58] initialised with a learning rate of 10^{-5}, a linear learning rate scheduler and 10% of training used as warm-up steps. The cross-entropy weights were calculated as in Equation 3, where $\mathbf{c}$ is a vector containing the number of samples in each class, and $\mathbf{w}$ is a vector containing the relevant cross-entropy weight.

$$w_i = \frac{\max(\mathbf{c})}{c_i} \tag{3}$$

Using these hyperparameters was found to provide a good balance between model performance and training time on the hardware used with the weighted cross-entropy loss.

In order to evaluate the models, the following metrics are reported: macro-averaged F1 score, precision and recall. These are all described for each class in Equations 4, 5 and 6 where TP is the number of true positives, FP is the number of false positives and FN is the number of false negatives. The arithmetic mean can then be taken for each class to provide a holistic overview of the model's performance.

$$F1 = \frac{2TP}{2TP + FP + FN} \tag{4}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{6}$$

Generally the macro-averaged F1 score is the standard to evaluate a multi-class classification problem, including ARI systems [6, 15, 51], where only a single metric is

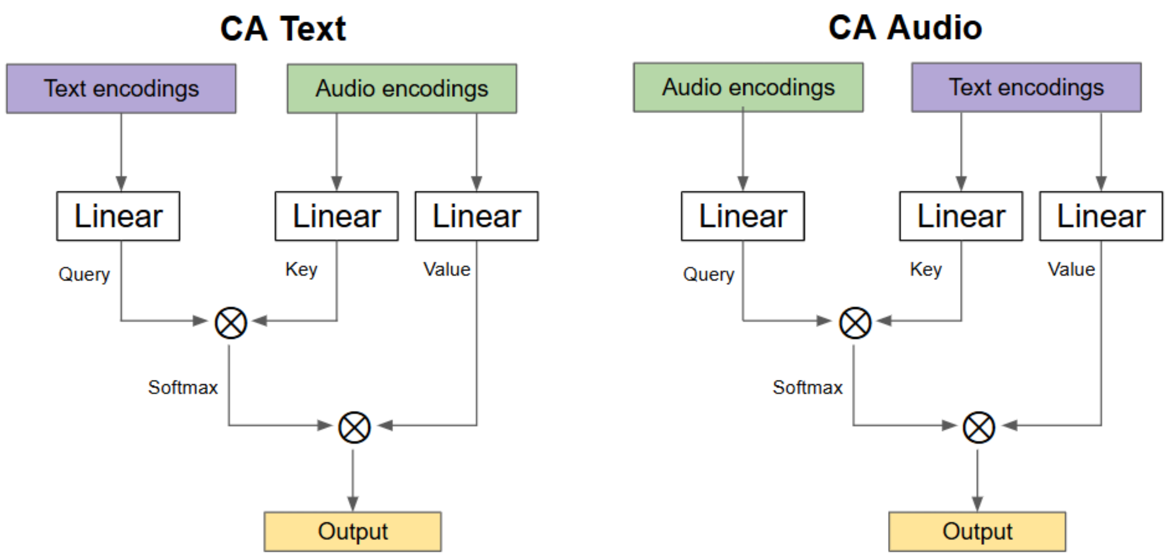


Figure 11: Crossmodal attention system with both text and audio queries. $\otimes$ is used to denote matrix multiplication.

reported, it will be a macro-averaged F1 score for this reason.

To provide a useful evaluation and simulate a real-world environment, the QT30-MM dataset is split into three splits: train, validation and test. 70% of the data is allocated for training, 10% for validation and the remaining 20% for testing. The model is evaluated on the validation split after every training epoch, the best performing model, based on macro-F1, is then chosen to be tested on the testing split, the metrics are then calculated and reported in the following sections.

After training, each model is then evaluated on the complete dataset for each Moral Maze episode (Banking, Empire, Money, Problem, Syria, Green Belt, Hypocrisy and Welfare) and each metric calculated to provide an overview of the cross-domain performance of the model.

In order to evaluate the different methods to sample unrelated arguments as described in Section 3.1.4. Models are trained on SCS, US and LCS, the validation dataset is sampled identically to the training set, and tested, both in-domain and cross-domain on SCS. This is used because of its description as a more realistic problem [51]. All code used for the experiments can be found on GitHub[9].

5.2 In-Domain

Results are reported for both the 3-class problem (considering support, attack and no relation) and the 4-class problem (considering RA, CA, MA and NO). First results are considered when evaluating in-domain, i.e. on the test set of the QT30-MM dataset. Only macro-f1 scores are reported here, precision and recall scores are also reported in Appendix B.

5.2.1 The 4-Class Problem

Table 8 shows the macro-f1 scores of each model using RoBERTa-base as the text encoder and Wav2Vec2-base as the audio encoder. All that is shown are the results for models performing early sequence fusion across different NO-sampling strategies. In the 4-class problem it does not seem that the addition of acoustic features makes much if any difference to the performance of the

[9] https://github.com/Syn-Tax/cross-domain-am

model on the ARI task. This result has also been found by others [7].

In some runs, the audio only models do not learn above the performance of the random baseline, it is unclear why this occurs but it appears to be random. Comparing the NO-sampling strategies there does not seem to make an appreciable difference when tested on SCS. Because SCS is considered a much more challenging task [51] it would not be expected that models trained on LCS or US would perform nearly as well as those trained on SCS, however, this does not seem to be the case. The result of this experiment implies that regardless of the sampling strategy the model is able to acquire the same knowledge and would likely perform similarly in a real-world setting, it is simply that SCS evaluations are harder than US evaluations which in turn are harder than LCS evaluations.

Table 8: Macro-F1 scores for early sequence fusion models on the 4-class problem. Highest results in each column are shown in bold.

Model	SCS	LCS	US
Text Only	**.58**	**.59**	**.59**
Audio Only	.43	.41	.20
Concatenation	**.58**	.57	.58
Product	.56	.57	.58
CA Text	.57	.46	.57
CA Audio	**.58**	.57	.57
Random	.22	.23	.24
Majority	.14	.14	.14

The different sequence fusion techniques are also compared in Table 9. Here it can be seen that early sequence fusion techniques outperform late fusion techniques by approximately 50% for both text only and audio only with concatenation showing greater improvement at approximately 60%. This increase in performance is likely attributed to the fact that when the sequences are fused before the attention mechanisms are applied the model is able to make the long-range dependencies across sequences. This comes in contrast to the fact that the model is unable to make any dependencies cross-sequence when they are fused after the attention mechanisms are applied.

Table 9: Macro-F1 scores across sequence fusion types when trained on SCS on the 4-class problem.

Model	Early	Late
Text Only	.58	.36
Audio Only	.43	.28
Concatenation	.58	.38
Random	.22	
Majority	.14	

What follows is a more in-depth discussion of the results with the hope that it will yield some understanding of the models' limitations and how they could be improved. In order to do this the text only model trained on SCS is explored in detail, however, the conclusions were found to hold on other models. A good place to begin here is by analysing the class F1 distribution, here F1 scores are reported for each of the four classes (NO, RA, CA and MA). As can be seen in Table 10 the model performs significantly worse when shown a conflict relation as opposed to the other possible classes. It is possible that this is due to the significant class imbalance present in almost all ARI datasets as discussed in Section 3.

Table 10: Class F1 distribution for text only SCS model.

NO	RA	CA	MA
.76	.60	.30	.66

A further analysis can be conducted by looking at the confusion matrix generated as shown in Figure 12. The ideal confusion matrix shows a diagonal line, in this case from the top left down to the bottom right of the matrix, and can be used to determine which classes the model struggles to distinguish. For ARI, it is generally expected that the model is able to distinguish CA from other classes, while RA and MA are often confused with each other and sometimes with NO. This follows from the difficulties that human annotators have when determining the different relations [1]. However, this is not what Figure 12 shows, instead the model is generally confusing most classes, most notable is the underprediction of the CA class. This implies the model is simply predicting the majority classes which is a well known and well studied problem in all classification problems involving unbalanced data [59]. Typically such problems are relatively simple to solve, often using either weighted loss functions (as is explained in Section 5.1) or some form of data augmentation or manipulation technique. During this project, primarily random resampling was experimented with. Random resampling generally involves a combination (or only one) of oversampling minority classes (e.g. randomly duplicating samples labelled as CA) or undersampling majority classes (e.g. randomly discarding samples labelled as RA or NO). Often this has been shown to be the best technique for solving class-imbalance problems, despite the rise of other resampling techniques (such as SMOTE) [60]. Unfortunately in this case no resampling distribution could be found to meaningfully improve the model performance.

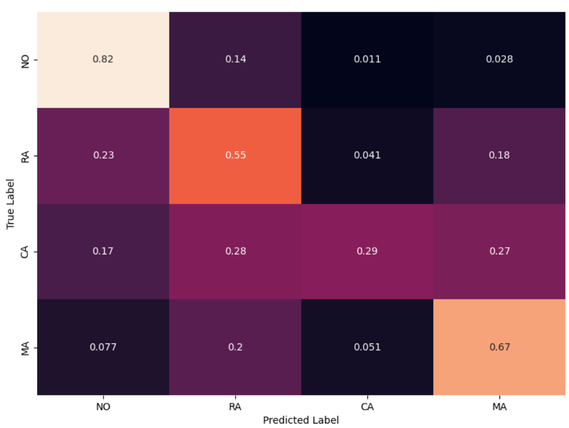


Figure 12: Confusion matrix showing true and predicted labels for the text only SCS model.

5.2.2 The 3-Class Problem

Table 11 shows the macro-f1 scores across each NO-sampling strategy for the 3-class problem using RoBERTa-base as the text encoder and Wav2Vec2-base as the audio encoder. Similarly to the 4-class problem, the addition of acoustic features to not seem to make an appreciable difference to the performance of the model. However, it is still useful to discuss the results in more detail, again using the text only model trained on SCS.

Table 11: Macro-F1 scores for early sequence fusion models on the 3-class problem. Highest results in each column are shown in bold.

Model	SCS	LCS	US
Text Only	**.62**	.59	.61
Audio Only	.21	.54	.22
Concatenation	.61	.61	.60
Product	.58	.61	.62
CA Text	.53	.53	.52
CA Audio	.61	**.62**	**.63**
Random	.28	.30	.29
Majority	.22	.22	.22

Table 12 shows the results when considering the different sequence fusion techniques. It can be seen that early fusion techniques significantly outperform late sequence fusion. Similarly to the 4-class US run, the early audio only model was not able to learn during this run. For both the text only and multimodal models, early fusion improves upon late fusion by approximately 44%.

Table 12: Macro-F1 scores across sequence fusion types when trained on SCS on the 3-class problem.

Model	Early	Late
Text Only	.62	.43
Audio Only	.21	.33
Concatenation	.61	.43
Random	.23	
Majority	.15	

What follows is a more in-depth analysis of the 3-class in-domain results. The class F1 distribution for the 3-class problem is shown in Table 13. Similarly to the 4-class F1 distribution, the Attack class appears to be significantly harder to prodict than the other classes. Similarly to the 4-class problem it can be hypothesised that this is due to the class imbalance in the dataset. What is interesting, is the fact that the class F1 scores for the Attack/CA relations have dropped when compared with the 4-class results and the scores for non-attack/CA relations have risen. It is possible that this is simply due to the change in the number of classes, however, it can also be considered that the 3-class dataset is more heavily unbalanced against the Attack relation which could also have this effect.

Table 13: Class F1 distribution for text only SCS model on test split.

None	Support	Attack
.82	.78	.26

The confusion matrix for the 3-class problem, as shown in Figure 13 can also be discussed. Here the underprediction of the attack class and the overprediction of the majority class. When compared to the 4-class confusion matrix (Figure 12) it appears that the model is effectively combining incorrect predictions between samples labelled inference and rephrase. This result could imply that the model's learning is approximately equivalent between the 3- and 4-class approaches, although it should be noted that more investigation is required to prove this.

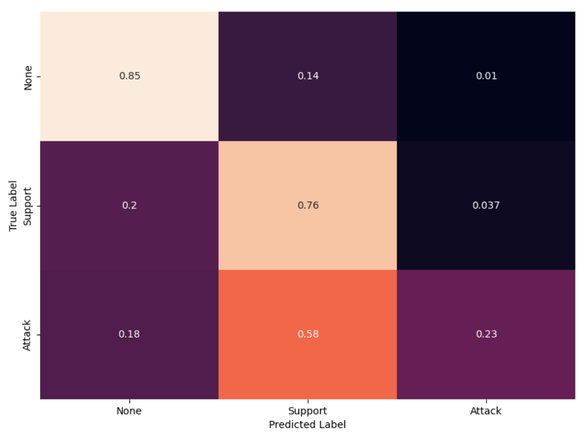


Figure 13: Confusion matrix showing true and predicted labels for the text only SCS model.

5.3 Cross-Domain

In this section the results presented in Section 5.2 are extended across the Moral Maze subcorpora. Results here are presented across each subcorpus and the arithmetic mean calculated and also reported. The goal of this section is to analyse how well the models and techniques are able to generalise into different topics and domains. Similar to the In-Domain results, first the 4-class problem is discussed and then its 3-class equivalent. Only the Macro-F1 scores are reported here with precision and recall scores added in Appendix B.

5.3.1 The 4-Class Problem

Table 15 provides a cross-domain evaluation of the different model architectures across the nine Moral Maze subcorpora when trained on SCS. Taking a broad overview, there is a distinct lack of significant improvement when the addition of acoustic features is considered. Since the evaluation is significantly harder than evaluating in-domain, the models show a significant decrease in the macro-F1 scores when comparing back to the in-domain results. This drop shows how challenging it is for the models to generalise effectively across the different domains.

Table 14: Mean cross-domain macro-F1 scores for early sequence fusion models on the 4-class problem across different sampling strategies. Highest results in each column are shown in bold.

Model	SCS	LCS	US
Text Only	.46	**.46**	**.46**
Audio Only	.37	.36	.22
Concatenation	.45	.43	.45
Product	.45	.44	**.46**
CA Text	.43	.32	.41
CA Audio	**.47**	**.46**	.43
Random	.23	.23	.23
Majority	.15	.15	.15

Table 16 compares early and late sequence fusion in a cross-domain setting. The results reported are the arithmetic mean across the Moral Maze subcorpora. Generally the increase is similar to that found in the in-domain evaluation with approximately a 50% increase for the text only and multimodal models and a 32% increase in performance for the audio only model.

Table 14 can be used to compare the different NO-sampling strategies which again, seem to show little difference between the various methods, both for unimodal and multimodal approaches. Similarly to the in-domain

Table 15: Cross-Domain macro-averaged F1 scores on 4-class SCS trained models. Best scores in each column are shown in bold.

Model	B	E	M	P	S	G	H	W	Mean
Text Only	.44	.46	**.48**	.42	.43	.50	**.51**	.41	.46
Audio Only	.34	.37	.39	.38	.33	.38	.40	.37	.37
Concatenation	.43	.43	.45	**.45**	.45	.49	.45	.43	.45
Product	.41	.44	.42	.42	**.46**	**.52**	.46	.43	.45
CA Text	.40	.44	.44	.40	.42	.49	.43	.44	.43
CA Audio	**.45**	**.49**	.44	.42	.45	.53	.48	**.46**	**.47**
Random	.19	.23	.20	.19	.22	.25	.21	.24	.23
Majority	.16	.15	.15	.15	.15	.14	.15	.14	.15

Table 16: Macro-F1 scores across sequence fusion types when trained on SCS on the 4-class problem. The mean is taken across all Moral Maze subcorpora.

Model	Early	Late
Text Only	.46	.30
Audio Only	.37	.28
Concatenation	.45	.30
Random	.23	
Majority	.15	

Table 17: Class F1 distribution for text only and CA audio SCS models on banking subcorpus.

Model	NO	RA	CA	MA
Text Only	.67	.60	.41	.065
CA Audio	.65	.64	.41	.095

results, what follows is a close look into the results of both the text only and CA audio models when trained on SCS and evaluated on the Banking subcorpus.

The class F1 distribution can be found in Table 10. Similarly to the in-domain results, the model is very able to predict unrelated pairs and pairs connected by an inference, and the score for pairs connected by a conflict are similar. The major difference in the class distribution is the inability of the model to accurately predict rephrases, it is possible that this is the result of an increase in domain specific knowledge and terminology necessary to predict these rephrases but these data are in no way conclusive in that respect.

Figures 15 and 14 show the confusion matrices for both the text only model and the CA audio model when trained on SCS and evaluated on the Banking subcorpus. While the matrices are generally very similar, there are some notable differences that show as a trend across all subcorpora. Firstly the crossmodal attention model is better able to distinguish the rephrases. The text only model seems to be more likely to predict MA for true CA or RA samples. The other notable distinction between the two models' performance is that the text only model is more likely to confuse conflict-labelled pairs as being unrelated, as opposed to the crossmodal attention model which is more likely to predict the label as an inference in all cases. Similarly to the in-domain results, there was no resampling of the training data that could be found to change the F1 distribution across classes.

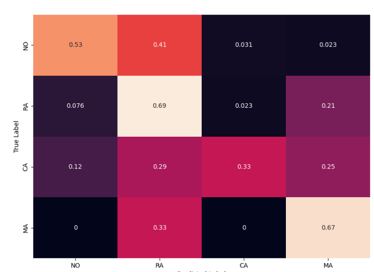


Figure 14: CA Audio model confusion matrix on the banking subcorpus.

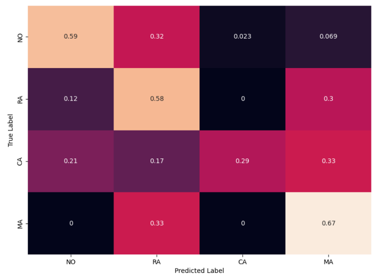


Figure 15: Text only model confusion matrix on the banking subcorpus.

5.3.2 The 3-Class Problem

Next, the data from the 3-class problem is extended across different domains. The data can be seen in Table 20. Generally the results are similar to the 4-class problem with a similar drop in macro-F1 scores from the in-domain results. Although the 3-class problem is slightly easier than the 4-class problem, the drop in performance is still roughly similar.

Table 18 allows a comparison between early and late sequence fusion methods on the 3-class problem. Here for both the text only and multimodal approaches early fusion improves performance by around 40% whereas the early audio only model did not learn effectively. It should be noted that although generally achieving lower performance, the late fusion models were always able to learn when only trained on audio data.

Table 18: Macro-F1 scores across sequence fusion types when trained on SCS on the 3-class problem. The mean is taken across all Moral Maze subcorpora.

Model	Early	Late
Text Only	.54	.38
Audio Only	.21	.33
Concatenation	.54	.40
Random	.23	
Majority	.15	

What follows is another discussion regarding the detailed results of the CA Audio model and the text only model. First, the class F1 distribution can be found in Table 19. Here, as could reasonably be expected, the results differ significantly from the 4-class problem. The model is able to effectively classify the support relations and no significant drop is observed when compared to the in-domain results. However, the drop in macro-F1 seems to originate from the drop in the model's ability to classify unrelated nodes.

Table 19: Class F1 distribution for text only and CA audio SCS models on banking subcorpus.

Model	None	Support	Attack
Text Only	.66	.72	.26
CA Audio	.58	.69	.29

Figure 16 shows the confusion matrix for the CA audio model when evaluated on the banking subcorpus. Much like what was seen in Section 5.2.2 the matrix is characterised by the overprediction of Support relations, with the main difference being that this overprediction is worse than when evaluated in-domain.

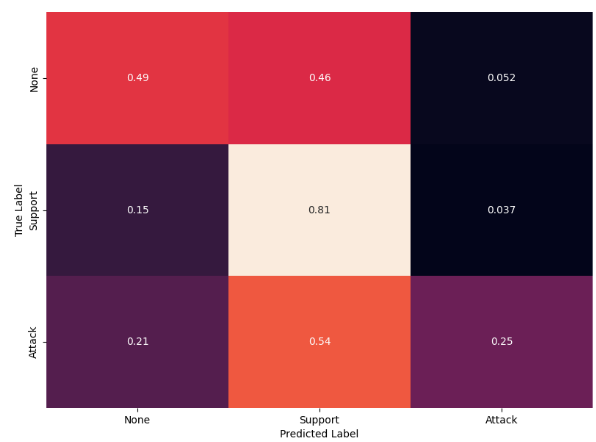


Figure 16: CA Audio model confusion matrix on the banking subcorpus.

6 Limitations

Models Throughout the project there is a distinct lack of comparison between different encoder models both

Table 20: Cross-Domain macro-averaged F1 scores on 3-class SCS trained models. Best scores in each column are shown in bold.

Model	B	E	M	P	S	G	H	W	Mean
Text Only	.54	.47	.50	**.50**	.58	.55	.63	.51	**.54**
Audio Only	.21	.20	.22	.21	.20	.21	.22	.21	.21
Concatenation	.58	**.49**	.47	**.50**	.57	**.57**	.59	.49	**.54**
Product	.51	.45	.44	.47	.53	.54	**.64**	.47	.51
CA Text	.43	.40	.43	.41	.44	.46	.47	.44	.44
CA Audio	**.59**	.44	**.52**	.48	**.59**	.54	.60	**.52**	**.54**
Random	.27	.32	.30	.27	.30	.29	.29	.33	.30
Majority	.21	.21	.22	.21	.20	.21	.22	.20	.21

from a text and an audio perspective. While it is likely that the general overarching conclusions would still hold for other encoders it is very possible that the more specific conclusions could be encoder-specific. This leads into the fact that only the base versions of RoBERTa and Wav2Vec2 are used, it has been shown that using the large models has increased performance both in-domain and cross-domain for text only tasks [15].

Forced Alignment Through the use of forced alignment technologies it is very possible for an amount of accuracy to be lost, especially when considering the poor environments in which such a system will have to perform in the real world (i.e. with lots of crosstalk, a wide range of accents and regional dialects etc.). While the data presented here have been proven to be correct to a certain degree, it is not possible to completely guarantee correctness.

Statistical Significance Because of the time constraints of this project, only a single run could be performed for each reported result. Therefore it is impossible to tell whether any comparison is statistically significant, however, given the size of the major conclusions made it is very likely that they still hold.

7 Conclusions

When considering goal (i) as stated in Section 1, as a result of this project, two major argumentative corpora have been extended with acoustic features into multimodal datasets for use in many areas of argumentative research. This includes the large QT30 corpus, of which a multimodal subset (QT30-MM) is presented, and the much smaller, cross-domain Moral Maze corpus. QT30-MM is the largest dataset for the ARI task which is currently available.

Goal (ii) of this project was to use the created datasets to conduct an evaluation of different multimodal techniques in a cross-domain setting, comparing early and late sequence fusion and various different late multimodal fusion techniques. Through this evaluation it was found that the addition of acoustic features does not improve the performance of argument relation identification systems in-domain and does not improve the models' ability to generalise across multiple domains.

Although acoustic features were not useful for ARI, it was discovered that the sequence fusion technique chosen during model creation is vitally important for the performance of the model. By combining the sequence data early in the process (before encoding) the model is able to make cross-sequence dependencies and therefore significantly improves performance on ARI.

Counterintuitively, all models struggle to distinguish the attack/conflict relations, it is unclear why this occurs however, since data augmentation techniques had no effect it appears unlikely that it is due to the dataset imbalance present. Generally the areas with which the models struggle do not seem to match human intuition, nor how human annotators struggle with the task. When considering the cross-domain results on the 4-class problem, while the models still struggle distinguishing conflict relations, they struggle even more with rephrases, often incorrectly predicting conflicts as rephrases, or predicting rephrases as inferences.

Through the discussion of techniques used to sample unrelated node pairs they have little difference in-domain indicating that the models are able to gain the same knowledge and understanding regardless of the sampling method used, it is simply the difficulty of the evaluation which changes. This supports previous conclusions that the sampling method is an important consideration when creating and evaluating ARI systems [51].

The results presented also compare different multimodal fusion strageties showing that simple concatenation, an elementwise product and a crossmodal attention mechanism all perform well. The performance of the crossmodal attention mechanism does vary depending on which modality is used for queries (and by extension keys and values), it was found that the mechanism performs best when text is used to generate keys and values while audio is used to generate the queries.

8 Future Work

To provide a more holistic view of this topic in the future, it would be useful to further understand the importance of different encoders and with that whether the varying pre-training strategies have an influence on the ability of the model to generalise across domains. Another possible extension would be to consider data processing and classification methods which preserve inference and conflict structures as discussed in Section 3.1.1.

With the recent boom in LLMs and especially multimodal LLMs they provide an opportunity in terms of their potential ability to generalise across domains with minimal amounts of learning (e.g. using in-context learning). LLMs have already shown promise in argument mining tasks so it seems an appropriate next step to discover how they fair in a cross-domain environment [11].

9 Legal, Social, Ethical and Professional Issues

With the recent increases in the availability of AI technologies the considerations around the ethical and social uses of such systems has come under scrutiny. Much of this scrutiny relates to how these intelligent systems can be created and used ethically. Due to the power of AI systems they are an incredibly useful tool across many fields, heavily reducing the workload and increasing the productivity of many people, on the other hand, however, because of this power even relatively incompetent, malevolent actors have the ability to cause damage. Before the introduction and increase in the availability of LLMs, malevalent actors had to be quite competent in order to cause damage, that has however changed because of the ease of use of such systems.

It is often possible to cause damage simply through laziness. This has been seen in the author's previous work in education, where overrelience on AI systems and assistants can cause a significant decrease in accuracy, in systems where the use of 'human-in-the-loop' type systems are used with the goal to increase efficiency while still maintaining accuracy and minimising mistakes. Such a system only works if a. the tools are used correctly and b. the human does not become complacent and therefore accuracy falls in relatively critical situations. This is also a discussion worth having in AM specifically with the release of interactive assistants for the task [61]. With the introduction of openly-useable LLMs such as OpenAI's Chat-GPT models, many people are using these systems as 'life-assistants' and thus this overreliance does not have bounds in any specific field but rather life as a whole.

Another consideration is the creation and training of such systems, specifically around the data required. Primarily this comes down to how the training datasets are sourced, created and annotated (where annotation is required) and whether this is both legal and ethical. The details of the annotation of the data used in this project can be found in the individual datasets' papers, however, it was ensured that all data from those datasets was annotated and sourced ethically. The sourcing of data is also an important consideration, especially surrounding the license under which the original data are released. This generally becomes a problem when using the data for commercial purposes (i.e. creating commercially available models). Throughout this project it was ensured that all training data has been sourced within the terms of any licenses.

There is also an environmental implication around training large models, especially around the power usage when training large models (especially LLMs). It is therefore important that the power sources are considered by organisations developing these incredibly large models.

Considering the social implications, LLMs are starting to be used in a 'personal assistant' capacity, including responding to emails or messages for the user. This immediately produces a lack of trust in the authenticity of such messages since the goal is generally to talk to the user.

Acknowledgements

I would like to thank my supervisor Dr. Ramon Ruiz-Dolz for his unfailing support and advice throughout this project, and the rest of the Centre for Argument Technology at the University of Dundee for their advice and knowledge in the subject. I would also like to thank all of my friends and family without whom life would be a misery.

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A Datasets

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