Multimodal Prediction of Spontaneous Humour: A Novel Dataset and First Results

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Abstract—Humour is a substantial element of human affect and cognition. Its automatic understanding can facilitate a more naturalistic human-device interaction and the humanisation of artificial intelligence. Current methods of humour detection are solely based on staged data making them inadequate for ‘real-world’ applications. We address this deficiency by introducing the novel Passau-Spontaneous Football Coach Humour (Passau-SFCH) dataset, comprising of about 11 hours of recordings. The Passau-SFCH dataset is annotated for the presence of humour and its dimensions (sentiment and direction) as proposed in Martin’s Humor Style Questionnaire. We conduct a series of experiments, employing pretrained Transformers, convolutional neural networks, and expert-designed features. The performance of each modality (text, audio, video) for spontaneous humour recognition is analysed and their complementarity is investigated. Our findings suggest that for the automatic analysis of humour and its sentiment, facial expressions are most promising, while humour direction can be best modelled via text-based features. The results reveal considerable differences among various subjects, highlighting the individuality of humour usage and style. Further, we observe that a decision-level fusion yields the best recognition result. Finally, we make our code publicly available at https://www.github.com/EIHW/passau-sfch. The Passau-SFCH dataset is available upon request.

Index Terms—Humour, Multimedia, Dataset, Affective Computing, Sentiment Analysis, Computer Audition, Computer Vision, Natural Language Processing

1 INTRODUCTION

HUMOUR can be defined as a communicative expression that establishes surprising or incongruent relationships or meaning and is intended to amuse [1,2]. Humour is arguably one of the key aspects of human communication, and characterised by its multifaceted nature. Whether in form of a simple punchline or humorous non-verbal behaviour within a conversation, humour can be used in a variety of ways and can have strong effects on the mental states of the interlocutors, making it a powerful form of interaction [3,4]. In fact, humour not only impacts individuals, but also group behaviour and group dynamics. For example, humour has been shown improve team performance in companies when managers use it properly [5]. More generally, humour can foster social exchange, stress relief [6] and creativity [3].

Numerous disciplines, including sociology [6], psychology [7,8], philosophy [9], and neuroscience [10] have investigated humour from different perspectives. In computer science and, especially, affective computing, the automatic measurement of humour has attracted increasing research interest in recent years, e.g., [11,12,13]. In particular, humour has been identified as important in human-computer interaction [14,15]. Because of the ubiquity of humour in our everyday interpersonal interactions, its automatic measurement is highly relevant [3].

Humour can be expressed in a variety of ways and modalities. An utterance can be perceived as humorous due to its semantic content (text), accompanying gestures or facial expressions (visual signals), variations in voice (audio signal) or a combination thereof. Automated Machine Learning (ML)-based humour recognition can exploit this multimodality of humour by taking the textual, visual, and acoustic modalities into account, e.g., [13].

In addition, lightweight ML frameworks such as DeepSpectrumLite [16] enable an on-device humour recognition [16].

Previously presented multimodal ML approaches are based on datasets in which humour is used in a scripted context, e.g., data collections from TED Talks [17] or TV series [18,19]. To the best of our knowledge, there is no database allowing for an automated detection of spontaneous humour. This poses a difficulty as spontaneous in-the-wild humour may substantially differ from planned humour in a scripted scenario. Moreover, existing datasets typically only come with a simple, binary label scheme indicating presence of humour.

To address these shortcomings, we contribute with this work by introducing the novel Passau Spontaneous Football Coach Humour (PASSAU-SFCH) dataset which is based on press conferences – and hence, non-scripted communication – of professional football coaches from the German Bundesliga (the national premier soccer league). PASSAU-SFCH includes annotations according to the Humour Style Questionnaire (HSQ) proposed by Martin et al. [20]. We com-
pare the PASSAU-SFCH dataset to other humour detection databases and provide deeper insights into the data.

Furthermore, we extract an extensive set of features for the audio, video, and text modalities. Based on that, we conduct a series of ML experiments on automatically analysing the spontaneous use of humour in PASSAU-SFCH.

2 RELATED WORK

Early approaches to automatic humour recognition focused on textual data only. We give a brief overview of them in Section 2.1. Recently, multimodal approaches, discussed in Section 2.2, have attracted increasing interest.

2.1 Textual Humour Recognition

Humour recognition is a vivid subfield of Natural Language Processing (NLP). First attempts to text-based humour recognition can be traced back to 2004 when Taylor and Mazlack [21] investigated wordplay in jokes utilising N-grams. In 2005, Mihalcea and Strapparava [22] introduced a dataset of humorous and non-humorous one-liner sentences sourced from the web alongside machine learning approaches to predict whether a sentence is humorous or not. Another dataset often used is the Pun of the Day dataset created by Yang et al. [24], consisting of puns scraped from a website and non-humorous data acquired from, amongst others, news websites. Recently, social media data became a popular source for textual humour datasets, with datasets based on tweets [25] and Reddit posts [11] being proposed. While the majority of the available datasets are in English, corpora in Italian [27], Spanish [25], Chinese [28], and Russian [29] have been created. Typically, these datasets come with a binary labelling, i.e., texts are annotated on whether they are humorous or not. This is different in, e.g., #HashtagWars [24] and the dataset by Castro et al. [25], where texts are annotated with different degrees of humour. For task 7 of SemEval-2017 [31], English puns have been labelled for the location and interpretation of the word being responsible for the pun. Task 7 of SemEval-2021 [32] introduced a dataset in which social media posts are not only labelled for humorous intention, but also regarding controversy and offensiveness. Another approach to creating text-based humour recognition datasets is headline editing. [33] West and Horvitz [33] let annotators edit a funny news headline into a serious one, while Hossain et al. [34] reverse this process, encouraging annotators to modify a serious headline into a funny one.

Earlier textual humour recognition approaches relied on handcrafted features such as antonymy or alliterations and machine learning models like Support Vector Machines (SVMs) and Random Forests [22] [23]. In recent years, Deep Neural Networks (DNNs) have been employed. To give an example, Chen and Soo [28] build a Convolutional Neural Network (CNN), while Ren et al. [35] propose an approach based on Long Short-Term Memories (LSTMs) and an attention mechanism. With the advent of large pretrained transformer language models like BERT [36], the focus of textual humour detection shifted towards such models, motivated by their promising performance in many NLP downstream tasks. For example, Weller and Seppi [11] finetune BERT for the recognition of jokes. Similarly, [37] make use of BERT sentence embeddings to tell jokes and non-jokes apart.

2.2 Multimodal humour recognition

Even though scholars have made promising attempts to model humour based on texts alone, semantics is only one aspect of an utterance. Especially when it comes to more natural scenarios like dialogues between people, voice and mimic often complement the semantic content of an utterance and may help both humans and machine learning models to better grasp whether an utterance is meant to be humorous or not. However, the investigation of multimodal approaches to humour recognition gained traction considerably later than text-only humour recognition. To the best of our knowledge, Bertero and Fung [18] were the first to create a multimodal dataset for humour detection in 2016. They extracted dialogues from the TV sitcom The Big Bang Theory and utilised the canned laughter to automatically label them as being humorous or not. Similar datasets, also based on The Big Bang Theory and labelled using canned laughter, are created in [38] and [39]. In general, TV shows are a popular source for multimodal humour datasets. Wu et al. [19] introduce two datasets MUMOR-EN and MUMOR-ZH, constructed from the English sitcom Friends and a Chinese sitcom, respectively. MaSaC [40] consists of Hindi-English code-mixed sitcom dialogues manually annotated for the presence of humour as well as sarcasm. A different approach is presented in [41], where the authors obtained humour labels by exploiting time-aligned user comments for videos on the Chinese video platform Bilibili. Hasan et al. [17] compile their dataset UR-Funny from TED talk recordings, using laughter markup in the provided transcripts to automatically label punchline sentences in the recorded talks. For Open Mic, Mittal et al. [42] collected standup comedy recordings and used the audience’s laughter to create annotations indicating the degree of humour on a scale from zero to four. Similar to text-only datasets, most multimodal datasets are in English, notable exceptions being the already mentioned MUMOR-ZH [19], MaSaC [40], the Chinese dataset used in [41] and M2H2 [43], which is based on a Hindi TV show.

Regarding multimodal humour prediction, Bertero and Fung [18] experiment with CNNs and Recurrent Neural Networks (RNNs), but also Conditional Random Fields (CRFs). More recent approaches often use (self-)attention mechanisms to fuse representations of different modalities. For instance, the MuLOT model proposed by Pramanick et al. [12] employs attention within and across different modalities. Hasan et al. [13] obtain Transformer-based embeddings for the audio, video, and text modality and complement the latter with additional textual features inspired by humour theories. Further examples include the models introduced in [17], [40], [39], and [38]. The aforementioned methods were developed specifically for the humour detection task. Besides, models intended for multimodal sentiment-related tasks in general have been introduced and evaluated also for the humour detection task recently. Examples of such generic approaches are Multimodal Transformer (MuLT) [44], Modality-Invariant and -Specific Representations for Multimodal Analysis (MISA) [45], and Bi-
bimodal Fusion Network (BBFN) \[45\], which have all shown promising performance for the UR-Funny dataset.

A variant of PASSAU-SFCH was already featured in the MiSe-HUMOR subchallenge of the Multimodal Sentiment Analysis Challenge (MuSe) 2022 \[47, 48\]. Here, participants were tasked with predicting the presence of humour in PASSAU-SFCH. Participants could utilise the text, audio, and video modality. Several systems were proposed to tackle this task, all of them employing the Transformer architecture \[49, 50, 51\].

### 3 PASSAU SFCH Database

The PASSAU-SFCH database was originally created to develop a multimodal measurement of executive humour, i.e., humour utilised by corporate leaders. For at least two reasons it is particularly suitable to use date of press conferences by coaches of soccer teams for the purpose of automatic humour recognition.

First, a large amount of relevant data, including audiovisual recordings of press conferences, is publicly available. Second, football press conferences are quasi-experimental settings \[52\] including ad-hoc communication. Football coaches and journalists meet on a regular basis and follow standardised, structured procedures and rules, such as requirements for positioning of lights and a predetermined protocol of opening statement and question & answer format \[53\]. The standardised setting facilitates comparability across individual videos, different coaches, and time.

Sections 3.1 to 3.7 introduce the PASSAU-SFCH database in detail. Moreover, we discuss its differences to existing humour detection datasets in Section 3.8 and its limitations in Section 3.9.

#### 3.1 Collection

We collected 59 pre-match press conference videos of 10 Bundesliga coaches from the first 13 match days of the season 2017/2018. The videos are publicly available and were downloaded from the different clubs’ websites and social media presences. We ensured that videos only comprise the actual press conference, manually removing advertisements or waiting time without coaches and the like, if necessary. We aimed for our raw dataset to comprise at least 1 hour of communication for each of the 10 coaches. The number of press conferences per coach ranges from 3 to 11 because of difference in total press conference duration across clubs. Throughout this work, we refer to individual coaches by IDs from 1 to 10 for the sake of privacy.

As an important limitation, the coaches are all male, aged between 29–52 years (average 42 years) and of similar cultural background.

Table 1 displays statistics on the lengths of the individual recordings and recordings per coach. Importantly, our sample only includes native German speakers with full professional proficiency to mitigate the potential influence of different cultural contexts, a coach preference for certain communication content and style as well as audience’s reaction to their humour \[54\].

| # | μ (Duration) | σ (Duration) |
|---|--------------|--------------|
| subjects | 10 | 01:05:30 | 00:15:48 |
| videos | 59 | 00:11:06 | 00:06:51 |

The annotation process was split into an initial screening of the press conference videos, and humour-style annotation using DARMA \[59\].

With a rate of 2 Hz, the annotations are practically real-time. In line with the HSQ, one axis was dedicated to humour direction, the other to sentiment. The annotators were instructed not to cause any amplitude when no humour is present. Moreover, the annotators marked the segments in which the coach is speaking by pressing a button on the joystick which helps split the data into the relevant speaking time. Also, the annotators were able to pause the annotation process to ensure leeway for more difficult instances or any distractions.

#### 3.2 Transcriptions

We obtain transcriptions for every video in four steps. First, we generate automatic transcriptions via an XLSR-Wav2Vec2 model \[55\] fine-tuned on the German part of CommonVoice \[56\]. Especially depending on the degree of the dialect spoken by the subjects, we find the results to be of mixed quality.

Hence, in the second step, the automatic transcriptions were corrected manually. Third, in order to be able to align the transcripts to the videos, we use the Montreal Forced Aligner tool \[57\] to create timestamps on the word-level. Lastly, since we need the transcripts to be segmented into sentences for textual feature extraction, we apply the Transformer-based multilingual punctuation restoration model introduced by Guhr et al. \[58\] to the manually corrected transcriptions.

#### 3.3 Annotation

The videos are subsequently annotated by 9 trained annotators (5 female, 4 male) of similar age (average 25.33 years; range 23-31 years) and background.

The annotators received a thorough preparation through mandatory, full-day training, and an illustrative handbook. In the training, the annotators gained a theoretical understanding of humour and were provided with practical annotation examples.

As annotation scheme, we choose the two dimensions of humour of the HSQ proposed by Martin et al. \[20\], according to whom different styles of humour usage can be characterised by their sentiment – i.e., negative vs positive – and their direction – i.e., self-directed vs directed at others. This results in 4 different humour styles, as illustrated in Figure 1.

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1. https://huggingface.co/jonatasgrosman/wav2vec2-large-xlsr-53-german
2. https://huggingface.co/oliverguhr/fullstop-punctuation-multilang-large
Aggressive
Affiliative Self-Enhancing
Self-Defeating
❖ I don't have to work very hard at making other people laugh ... when I'm by myself, I'm often amused by the absurdities of life.

3.4 Preprocessing

Utilising the button annotations, we remove all parts of the video in which the coach is not speaking. This is necessary because we aim to predict humour solely based on data of the person in question, without considering possible reactions from the audience, especially laughter. After that, we are left with a dataset containing about 11 hours of video in total, with about an hour of video recordings per coach.

Regarding the annotation signals, we first apply thresholding to remove small, evidently erroneous amplitudes. Afterwards, the signals are clipped in order to account for outliers and subsequently min-max normalised. An annotation value is considered an outlier if it deviates from the mean by more than 2.5 standard deviations. We perform all these operations separately for each annotator and dimension (sentiment, direction). Moreover, because of the sparsity of segments considered humorous, we entirely ignore zero values in all of the computations mentioned above.

3.5 Agreement

The agreement is reported for both the sentiment and direction annotations. Moreover, agreement on whether humour was detected at all can be computed.

On average, about 4.4% of the sentiment annotations per rater are non-zero, with a standard deviation of 2.3%. Similar values can be observed for the direction labels, with a mean of 4.7% and a standard deviation of 2.1%. Because of this sparsity, we report the agreement only for the subset of the signals in which at least one annotator generated an amplitude for the respective dimension. For the agreement regarding sentiment and direction annotations, the Concordance Correlation Coefficient (CCC) is applied to the continuous signals. Comparing pair-wise different annotators, we obtain a mean pairwise CCC of 0.0985 for sentiment and a mean pairwise CCC of 0.0845 for direction. The standard deviations are 0.0485 and ±0.392, respectively.

In order to estimate the agreement on whether humour is present, we treat every annotation as humorous if there is an amplitude for either sentiment or direction, regardless of its sign. Since this yields binary labelling, the Intersection over Union (IoU) metric can be utilised to compare the annotators in a pair-wise manner. This results in a mean pair-wise IoU of 0.1554 with a standard deviation of 0.0433.

Figure 2 shows the mean pairwise IoU values for the detection of humour per annotator and coach. Overall, the agreement for all annotations is considerably low. Humour is only displayed occasionally by coaches during a press conference. Moreover, oftentimes this humour is, on the one hand, rather subtle, and, on the other hand, domain-specific, i.e., a basic understanding of football may not be sufficient to understand the evoked allusions and jokes. Another problematic aspect is that the type of humour may vary for different coaches. This intuition is supported by a closer look at the agreements for each coach.

As depicted in Figure 2, agreement is highly coach-dependent, with for example coach 9 displaying low mean IoUs compared to a relatively high agreement for, e.g., coach 5. Moreover, there are annotators who usually show a comparatively low agreement with other annotators, e.g., annotator 3. Depending on factors such as knowledge, norms and other cognitive structures, people perceive different events as humorous [7]. In other words, our annotation data reflect that the expression and perception of humour is highly contextual [60].

3.6 Gold Standard Creation

We first generate gold standard labels for sentiment and direction of humour by fusing the respective annotations
in every video. The following describes the gold standard creation procedure which was applied to both the sentiment and the direction annotations.

Let \( A = \{a_1, ..., a_b\} \) denote the set of annotators and \( N = \{n_1, ..., n_N\} \) the set of videos. We write \( x_{n,a} \) for the signal corresponding to the annotation of a video \( n \in N \) by a rater \( a \in A \).

Consistent with established practices for fusing continuous affect-related annotations [62, 63], we utilise a fusion method in the fashion of Evaluator Weighted Estimator (EWE) [64], i.e., we calculate agreement-based weighted sums from the individual annotators’ signals. Since agreement varies depending on the coach in question (cf. Section 3.5), we calculate agreement-based weighted means and standard deviations refer to the different coaches.

Our weightings \( w_a(c) \) then include two aspects of agreement. On the one hand, weights \( w_a(c)' \) based on the agreements between the annotator \( a \)'s and all other annotators’ signals are computed utilising CCC, as given in Equation (1). On the other hand, we consider agreement regarding the sheer presence of humour. For example, if annotator \( a \) disagrees with \( a' \) on whether an utterance is self- or others-directed, they still agree on the utterance being humorous. To account for this kind of agreement, another weight \( w_a(c)'' \) is calculated based on the signals’ absolute amplitudes, as can be seen in Equation (2).

\[
\begin{align*}
w_a(c)' &= \frac{1}{|A|-1} \sum_{a' \neq a} \text{CCC}(x_{N(c),a}, x_{N(c),a'}), \quad (1) \\
w_a(c)'' &= \frac{1}{|A|-1} \sum_{a' \neq a} \text{CCC}(|x_{N(c),a}|, |x_{N(c),a'}|). \quad (2)
\end{align*}
\]

In Equation (2), \( |\cdot| \) is meant to be an element-wise application of the absolute operator to a signal. The final weights \( w_a(c) \) are then computed according to Equation (3).

\[
w_a(c) = \frac{w_a(c)' + w_a(c)''}{\sum_{a' \in A}(w_{a'}(c)' + w_{a'}(c)'')}.
\]

Finally, the gold standard values for sentiment and direction are calculated as weighted sums.

Based on the fused annotations for sentiment and direction, a binary signal indicating the presence of humour can be computed. Any amplitude in any of the two dimensions is regarded as humour.

To account for small lags, we further apply a windowing approach with frame size 2 s and hop size 1 s to the fused sentiment and direction signals, resulting in 39,682 segments. Motivated by low Jaccard agreements for binary humour detection (cf. Section 3.5), we drop the three annotators with the lowest mean inter-annotator agreement per video. Each segment is labelled as humorous if at least 3 of the remaining 6 annotators have produced any amplitude for sentiment or direction within that segment.

For consistency, we use the same 2 s windowing approach to transforming the fused sentiment and direction signals. We reduce at most 4 values per window to one via mean pooling. Finally, all sentiment and direction segments are set to 0, if the corresponding humour label is 0.

### 3.7 Dataset Statistics

In total, 6.02% of the 39,682 segments are labelled as humorous. Different coaches display different amounts of humour in the recorded press conferences. Figure 3 clearly illustrates considerable differences in the usage of humour in general.

![Percentage of humorous segments per coach in the gold standard, partitioned by humour style.](image)

Table 2: Humour style percentages, based on humorous segments only. Means and standard deviations refer to the different coaches.

| Sentiment | negative | positive | \( \Sigma \) |
|-----------|----------|----------|-----------|
| self      | .0427    | .2229    | .2656     |
| other     | (.0443 ± .0338) | (.2084 ± .0845) | (.2528 ± .1022) |
| self-defeating | .2560    | .4759    | .7327     |
| self-enhancing | (.2337 ± .1113) | (.5109 ± .1123) | (.7457 ± .1031) |
| affiliative | .2995    | .6996    | .9990     |
|           | (.2784 ± .1070) | (.7205 ± .1068) |             |

### 3.8 Comparison with other Humour Datasets

In contrast to existing humour detection datasets, the subjects in our database act, in general, spontaneously, as they do not know in advance the exact questions they will be asked at the press conference. However, it can be argued that professional football coaches are used to handling such situations. Hence, it is reasonable to speak of a semi-staged situation here, in contrast to fully staged scenarios like acted TV shows, standup comedy, or TED talks.

Besides, our dataset is the first to include annotations according to the HSQ. While other datasets are labelled automatically, for example by using canned laughter [18, 38], or by three human annotators [19, 43], each video in our database has been labelled by the same 9 annotators. In
| Authors (Dataset Name) | Extra Labels | #Annotators | Dur. [h] | #Spk. | Lang. | % Humour | Scenario (scripted) |
|------------------------|--------------|-------------|----------|-------|-------|----------|-------------------|
| Bertero and Fung [15] (-) | - | ? (?-7) | en | 42.8 | Big Bang Theory (yes) |
| Yang et al. [41] (-) | - | 6.77 | 1 | zh | 26.72 | Bilibili platform (yes) |
| Hasan et al. [17] (UR-FUNNY) | - | 90.23 | 1741 | en | 50 | TED Talks (yes) |
| Mittal et al. [42] (OPEN MIC) | - | 3 | 17 | ? | en | 87.87 | Standup Comedy (yes) |
| Wu et al. [19] (MÚMOR-ZH) | - | 3 | 18.12 | 91 | zh | 28.36 | TV sitcoms (yes) |
| Wu et al. [19] (MÚMOR-EN) | - | 3 | 9.03 | 259 | en | 24.59 | TV sitcoms (yes) |
| Bedi et al. [43] (MASSAC) | Sarcasm | 3 | 80.98 | 5 | hi/en | 37.9 | TV show (yes) |
| Patro et al. [38] (-) | - | 84 | (?-7) | en | 82.5 | Big Bang Theory (yes) |
| Kayatani et al. [39] (-) | - | 77.7 | 10 | en | >25 | Big Bang Theory (yes) |
| Chauhan et al. [43] (M2H2) | - | 3 | 4.5 | 41 | hi | 33.74 | TV series (yes) |

### TABLE 3: Comparison of existing multimodal (audio, text, video) humour detection datasets and PASSAU-SFCH. Dur. denotes the overall duration of each dataset, #Spk. the number of speakers in it. Regarding the language abbreviations, zh stands for Chinese, hi for Hindi and de for German. Note that the OPEN Mic dataset by Mittal et al. [42] is special since it contains humour intensity ratings on a Likert scale (0-4) and uses recordings of TED talks as negative examples.

addition, to the best of our knowledge, PASSAU-SFCH is the first dataset for both textual-only and multimodal humour detection in German.

Humour is distributed comparably sparsely across the recordings in PASSAU-SFCH, with only 6.02% of the segments being labelled humorous. In other datasets, at least 24% of the annotated units are considered humorous. This sparsity is due to the rather matter-of-fact nature and objectives of press conferences.

In Table 3, we provide a detailed comparison of our dataset with other humour datasets.

An aspect not covered by Table 3 is the annotation level. Different from all existing humour databases except the one created by Yang et al. [41], PASSAU-SFCH is labelled in a time-continuous manner. All other datasets listed in Table 3 are annotated at utterance level, i.e., an utterance is either a punchline/joke or not. In PASSAU-SFCH, also due to the comparably natural setting, an utterance may consist of humorous and non-humorous segments.

### 3.9 Limitations

A significant shortcoming of PASSAU-SFCH is that the set of subjects in the recordings is both small and homogeneous. All 10 coaches are male, share a similar cultural background and work in the same profession. Moreover, their age spans only ranges from 29-52 years. A similar argument can be made regarding the demographically similar, non-random selection of annotators. Thus, many demographic groups are not represented in PASSAU-SFCH, probably limiting the generalisability of models trained on it.

Another limitation of our dataset is that though its setting is more spontaneous than in other existing datasets, the recordings are still, to a degree, staged. Press conferences are neither scripted nor truly ‘in-the-wild’ interlocutions and professional football coaches can be expected to usually handle such communicative situations in a polite, matter-of-fact way. The professional context of press conferences may also impact the humour style displayed by the coaches. For example, it is likely that coaches use aggressive humour less frequently in such a situation than in private.

Furthermore, the recordings are highly domain-specific which may especially impair generalisation in text-based approaches. The performance of text-based methods trained on PASSAU-SFCH may also suffer from the fact that press conferences are actually multi-party conversations while in PASSAU-SFCH, each video only comprises the data of one – albeit the most important – speaker per conference, i.e., the coach.

### 4 Experimental Setup

Our experiments are illustrated in Figure 4. In order to explore the strengths and weaknesses of all three available modalities, we compute three different contemporary feature sets for each of them. We then address the tasks of humour recognition as well as sentiment and dimension prediction. For the latter two, SVMs are used, while we employ Gated Recurrent Units (GRUs) for the recognition of humour. Given their simplicity and capacity to model sequences, GRUs are a natural choice for the task at hand. Note that for the experiments regarding sentiment and direction, only the segments labelled as humorous are considered. We opt for SVMs for these two tasks, after we observed massive overfitting with GRUs on the resulting comparatively small datasets. The focus of our experiments is on unimodal approaches, but we also conduct simple late fusions of trained models, gaining insight into the benefits of combining different modalities.

### 4.1 Features

Given the multimodal nature of humour, we make use of audio, video, and text data. For each of the three modalities, three different feature sets are computed, using both Transformers and more ‘conventional’ machine learning techniques.

#### 4.1.1 Audio

Regarding audio, we opt for the extended version of the Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) [65], DEEP SPECTRUM (DeepSpectrum) [66], and Wav2Vec2 (W2V) [67].

The eGeMAPS feature set comprises 88 speech-related paralinguistics features such as pitch, loudness, and Mel-Frequency Cepstral Coefficients (MFCCs). It has been successfully applied in Speech Emotion Recognition (SER)
“After the game, I know, one knows better”.

4.1.2 Text

For the textual features, we apply three pretrained transformer models, BERT [36], German SentimentBERT [82], and ELECTRA [83]. BERT [36] has already been used in the context of both text-only [11, 37] and multimodal humour recognition [58, 46]. Since the subjects of PASSAU-SFCH speak German, we employ a German version of BERT.

German SentimentBERT [82] is a Transformer model trained on German sentiment analysis data. Since sentiment is one of the two dimensions of the humour proposed in the HSQ, we hypothesise that German SentimentBERT might outperform the more generic models.

ELECTRA [83] is the third Transformer model which often outperforms the original BERT model in various NLP tasks [83]. For our experiments, we use a version of ELECTRA which is pretrained on German texts.

We carry out the same feature extraction procedure for all three models. An utterance is already segmented into sentences due to punctuation restoration. Sentence-level features are then obtained by averaging the last 4 layers’ representations for the special [CLS] token, following [84]. These features are aligned to the initial 500 ms annotations via the timestamps obtained from the Automatic Speech Recognition (ASR) output. The text feature for a 500 ms frame is the average over all – in practice, at most 2 – sentences intersecting with this frame. Besides, we also experimented with token-level features but found the results to be slightly worse than those for sentence-level embeddings.

4.1.3 Video

Because of the rather static press conference setting, we focus on face-related features for the video modality. This

3. https://github.com/audeering/opensmile
4. https://github.com/DeepSpectrum/DeepSpectrum
5. https://huggingface.co/jonatasgrosman/wav2vec2-large-xlsr-53-german
6. https://huggingface.co/bert-base-german-cased
7. https://huggingface.co/oliverguhr/german-sentiment-bert
8. https://huggingface.co/german-nlp-group/electra-base-german-uncased
is further motivated by the coaches’ faces typically being zoomed in on when the coaches are speaking. In the first step, we extract all faces using MTCNN [85] with a hop size of 500 ms in order to be in line with the 2 Hz annotations. We then make sure to only include the faces of the actual coaches. This is achieved by an automatic step, comparing FaceNet [86] embeddings of detected faces with embeddings of reference pictures. Subsequently, manual correction is carried out. Based on the extracted faces, three different feature sets are computed. Facial Action Units (FAUs) describe facial expressions. Ekman identified 44 such units and also proposed mappings from their activation to emotional states [87]. As FAUs play an important role in manual and automatic affect detection [88], we extract estimations of 20 different FAUs’ activations using the Py-FEAT toolkit [10].

Second, we extract latent facial features from a ResNet50 [89] trained on the VGGFACE 2 [90] face recognition dataset. A 512-dimensional feature vector is obtained by taking the representations of its last hidden layer.

Third, we apply FaRL for Facial Representation Learning (FaRL) [90] which is a pretrained Transformer model intended for tasks related to facial features. Using the FaRL image encoder we obtain 512-dimensional features for the extracted face frames.

4.2 Models

Using the obtained feature sets from each modality, we train two sets of machine learning models, namely a GRU-RNN approach for the detection of humour segments and a SVM approach for the recognition of sentiment and direction.

4.2.1 GRU-RNNs for Humour Detection

Since all features are extracted at a 2 Hz rate, each 2 s segment corresponds to up to 4 consecutive feature vectors. RNNs such as GRUs [91] are capable of modelling dependencies in sequential data and are thus a natural choice for this task.

For each of the 9 feature sets, we train 10 different GRUs, each time setting aside one coach as a test subject. This way, we can gain insights into the predictability of each coach’s individual humour style.

Hyperparameter searches, informed by previous results in [47, 48], regarding the number of layers, direction of the information flow (uni- or bidirectional), internal representation sizes and learning rate of the training process are conducted for each feature set individually. In the training process, we split the data of the 9 training coaches randomly into a train and development set. Every model is trained for at most 20 epochs but potentially stopped early after 5 epochs of no improvement on the development set. To mitigate the influence of random initialisation values, we repeat every training process 5 times with different, fixed random seeds. As a loss function, binary cross entropy is used. We choose AdamW [92] as the optimisation algorithm. The Area Under the Curve (AUC) is utilised as the evaluation metric, also as the early stopping criterion.

4.2.2 SVMs for Humour Style Classification

Moreover, we investigate whether the sentiment and direction of humorous utterances can be recognised automatically. For these experiments, we only take humorous 2 s segments into account. Since this limitation leaves us with only 2 387 data points, DNNs may not be a suitable choice. Instead, we train SVMs for both sentiment and direction prediction. We reduce both the sentiment and direction values to two classes \{-1, 1\}, framing both tasks as classification problems.

Because the features are extracted every 500 ms, they must be reduced to the 2 s label windows. This is achieved by computing the means of all feature values corresponding to a label window.

Analogously to Section 4.2.1 hyperparameter search is performed for every feature set separately in a leave-one-subject-out manner, always setting aside one coach for validation. Subsequently, in line with Section 4.2.1, 10 different models are trained for each feature set, each time leaving one coach out of the training data. We repeat every experiment with 5 fixed seeds.

As the evaluation metric, AUC is employed here as well. In order to obtain continuous predictions from SVMs, Platt Scaling [93] is applied.

4.2.3 Late Fusion

In order to explore the complementarity of different modalities, we conduct late fusion experiments for the recognition of humour as well as the prediction of both sentiment and direction. More specifically, we only consider the predictions obtained with the best performing feature of each of the three modalities (text, audio, video) and build new predictions for every coach as follows. First, we z-standardise each feature’s predictions. This is especially necessary for the predictions obtained by SVMs optimised for AUC, as different SVMs’ predictions may have different scales. Then, we compute a weighted sum where the weights are based on the performance during training. As for the SVM experiments, we take the AUC on the training set, reduced by .5000, i.e., chance level, as the weight. Regarding GRUs, the highest AUC encountered on the validation set during the training process is chosen as the weight, also reduced by .5000. We explore all possible combinations of modalities, namely audio+text, audio+video, text+video, and audio+text+video.

5 Results

We report the results for both the humour detection experiments with GRUs in Section 5.1. The SVM-based experiments regarding the prediction of humour style and sentiment are discussed in Section 5.2. Furthermore, we compare the results of all experiments across the different coaches in Section 5.3.

5.1 Humour Recognition

Table 4 lists the results for the binary humour recognition task addressed with GRUs.

All features lead to above chance performance for every coach. However, the AUC values differ considerably when comparing the three modalities.

9. https://github.com/timesler/facenet-pytorch 10. https://py-feat.org 11. https://github.com/WeidiXie/Keras-VGGFace2-ResNet50
TABLE 4: Results for binary humour prediction with different features with AUC as the evaluation metric. Mean and Std refer to the different coaches. More precisely, mean and standard deviations over the mean AUC (5 seeds) per coach are reported (standard deviations for every single coach’s 5 seeds are negligibly low). Analogously, Min and Max refer to the mean AUCs per coach. The column > Chance gives the percentage of coaches for which the mean AUC was above chance level, i.e., .5. The best results per modality are boldfaced, and the best unimodal and fusion results overall are underlined.

| Feature          | Mean (Std)  | Min   | Max   | > Chance |
|------------------|-------------|-------|-------|----------|
| Audio            |             |       |       |          |
| eGeMAPS          | .7003 (.0674) | .6037 | .8314 | 100 %    |
| DEEP SPECTRUM    | .6809 (.0782) | .5935 | .8494 | 100 %    |
| W2V              | .7504 (.0687) | .6173 | .8741 | 100 %    |
| Text             |             |       |       |          |
| BERT             | .7672 (.0531) | .7126 | .8919 | 100 %    |
| GERSSENT-BERT    | .7445 (.0602) | .6525 | .8854 | 100 %    |
| ELECTRA          | .8044 (.0689) | .7003 | .9169 | 100 %    |
| Video            |             |       |       |          |
| FAUs             | .8361 (.1022) | .5902 | .9509 | 100 %    |
| VGGFACE 2        | .8349 (.1048) | .6505 | .9480 | 100 %    |
| FaRL             | .8962 (.0766) | .7038 | .9625 | 100 %    |
| Late Fusion      |             |       |       |          |
| A + T            | .8283 (.0679) | .7361 | .9321 | 100 %    |
| A + V            | .8902 (.0696) | .7424 | .9822 | 100 %    |
| T + V            | .9027 (.0630) | .7734 | .9887 | 100 %    |
| A + T + V        | .9038 (.0600) | .7825 | .9903 | 100 %    |

All visual features’ means are higher than the mean value of any audio or text feature. One reason for the good performance of face-related features here may be that the coaches frequently smile or laugh during humorous utterances. It should be noted that laughter, with its meaning depending largely on the context of an utterance, does not necessarily imply humour. In the press conference setting, however, it might be more correlated to humorous utterances than in the wild. Among the video-based approaches, FaRL proves to be the best feature with a mean performance of .8902 AUC and the lowest standard deviation across all coaches. The expert-designed FAU features are outperformed by both deep learning based approaches VGGFACE 2 and FaRL.

Textual features fall behind the video-based ones with the best textual approach ELECTRA leading to a mean AUC of .8044. This can partly be explained by the domain-specific nature of the texts in question. The textual features are extracted using Transformer models pretrained on more generic texts and thus may fail to capture football-specific humour. Another limiting factor for predicting humour in this setting using only the transcripts is that the transcripts are incomplete, as they only contain the coach’s answers, but not the journalists’ questions. The questions are, however, a crucial aspect of each utterance’s context. Nevertheless, the performance of text-based features is, in general, more robust than for the other two modalities, with standard deviations across the coaches of at most .0089, namely for ELECTRA. Also, the lowest mean AUCs for an individual coach observed during the textual experiments, i.e., .6525 with GERSSENT-BERT, is higher than the lowest individual mean AUC of .5902 encountered with visual features.

The audio modality is less suitable for humour recognition, but still, all audio experiments result in AUCs over .5000. The performance of W2V is even comparable with that of BERT and GERSSENT-BERT. However, it should be noted that due to its speech recognition pretraining task, W2V embeddings also encode some linguistic information. Other than in the video experiments, the handcrafted eGeMAPS feature set leads to a slightly better result than the non-Transformer deep learning method DEEP SPECTRUM.

Of note, for each modality, the most recent feature extraction technology – all of them being based on Transformers – performs best.

Table 4 also demonstrates individual differences among coaches. It is clear from the reported standard deviations as well as minimum and maximum values that for some coaches, humour is harder to predict than for others. Notable discrepancies between the best and worst AUC per coach can be observed for every feature set. The differences range from about .1800 AUC for BERT to about .3600 for FAUs. Individual differences in predictability will be analysed more thoroughly in Section 5.3.

The results for different fusions prove that, to a degree, the three modalities are complementary. Fusing the best audio and text predictions outperforms the best text-only result with .8283 mean AUC compared to .8044. The video modality can benefit from being combined with text only as well as audio and text simultaneously, the latter leading to a mean AUC of .9038. Especially notable is the improvement regarding the minimum AUC values per experiment. In the best unimodal case FaRL, an AUC of .7038 is achieved for the worst-performing coach in this experiment. For the worst performing coach in the three-modal fusion experiment, however, an AUC of .7825 is observed, which marks a relative increase of more than 11 %.

5.2 Humour Style Classification
We analyse the results of the experiments described in Section 4.2.2 for the discrimination of humour direction and sentiment in Section 5.2.1 and Section 5.2.2 respectively.

5.2.1 Direction
In Table 5, the results for the experiments on distinguishing humour direction in humorous segments are presented. Different from humour recognition, the visual modality performs worst, with all features only marginally above or even below chance on average. The standard deviations and maximum values, however, show that for a few coaches, facial features actually encode information on whether humour is self- or others-directed. Similar phenomena can be observed in audio-based experiments. Here, more experiments yield results above chance, with DEEP SPECTRUM showing above-chance performance for 8 out of 10 coaches. On the one hand, the average audio results are only slightly larger than .5000 with no notable differences among the three different feature sets. On the other hand, there are coaches for which the audio modality alone is actually useful for predicting humour direction, as
features and the vast majority of textual experiments result to predict from facial expressions or acoustic signals alone.

In general, for each modality, higher AUC values than for direction prediction (cf. Table 5) are achieved. However, this does not hold for all individual features, as the mean performances of Deep Spectrum and BERT are slightly lower than in the direction experiments.

Here, the video modality yields the best results on average, with FaRL being responsible for the best mean AUC value in total.

The results for text, however, can compete with the visual ones, with ELECTRA as the best textual feature yielding .6446 mean AUC, thus outperforming VGGFace 2 with .6342 mean AUC. As expected by the construction of GesSent-BERT it outperforms the more generic BERT on the sentiment analysis task. Both visual and textual features almost always result in above-chance performance, the only exception being one coach for whom BERT fails with a mean AUC of .2603.

Acoustic features perform notably worse than visual and textual features on average, but at least the results for eGeMAPS always surpass chance level, while the W2V features fail to do so only for one coach. Moreover, the mean AUC of .5900 for eGeMAPS is higher than that of BERT. The relative superiority of textual features over acoustic ones is consistent with previous findings that the text modality is more suitable for valence prediction than acoustic data.

Differences among coaches can be observed here, too, indicated by the standard deviations and notable differences between the minimum and maximum AUC per coach for each feature, e.g., a difference of about .2600 for the FaRL experiments.

In the late fusion experiments, there is evidence that the modalities partly complement each other. The combination of textual and visual predictions leads to a mean AUC value.

Hence, it can be concluded that the direction of humour is mainly encoded in the semantics of an utterance.

### 5.2.2 Sentiment

Table 6 reports the results for sentiment prediction in humorous segments.

| Feature | Mean (Std) | Min   | Max   | > Chance |
|---------|-----------|-------|-------|----------|
| Audio   |           |       |       |          |
| eGeMAPS | .5900 (.0579) | .5277 | .7109 | 100 %    |
| Deep Spectrum | .5343 (.1085) | .2629 | .6613 | 70 %     |
| W2V     | .5500 (.1283) | .1873 | .6845 | 90 %     |
| Text    |           |       |       |          |
| BERT    | .5794 (.1165) | .2603 | .6932 | 90 %     |
| GesSent-BERT | .6141 (.0685) | .5175 | .7187 | 100 %    |
| ELECTRA | .6446 (.0542) | .5512 | .7296 | 100 %    |
| Video   |           |       |       |          |
| FAUs    | .6542 (.0749) | .5491 | .7884 | 100 %    |
| VGGFace 2 | .6342 (.0869) | .5127 | .7347 | 100 %    |
| FaRL    | .6597 (.0770) | .5531 | .8153 | 100 %    |
| Late Fusion |           |       |       |          |
| A + T   | .6576 (.0756) | .5920 | .7967 | 100 %    |
| A + V   | .6482 (.0732) | .5448 | .7732 | 100 %    |
| T + V   | .7100 (.0748) | .6074 | .8294 | 100 %    |
| A + T + V | .6998 (.0808) | .6023 | .8440 | 100 %    |

| Feature | Mean (Std) | Min | Max | > Chance |
|---------|-----------|-----|-----|----------|
| Audio   |           |     |     |          |
| eGeMAPS | .5496 (.1073) | .3964 | .7604 | 60 %     |
| Deep Spectrum | .5396 (.1178) | .2864 | .7656 | 80 %     |
| W2V     | .5314 (.0896) | .4167 | .7135 | 60 %     |
| Text    |           |     |     |          |
| BERT    | .6018 (.1054) | .4363 | .7784 | 80 %     |
| GesSent-BERT | .5756 (.1449) | .2240 | .7424 | 80 %     |
| ELECTRA | .6108 (.1081) | .4344 | .8281 | 90 %     |
| Late Fusion |       |     |     |          |
| A + T   | .6128 (.1100) | .3806 | .8229 | 90 %     |
| A + V   | .5493 (.1079) | .3923 | .7604 | 60 %     |
| T + V   | .6101 (.1074) | .4349 | .8281 | 90 %     |
| A + T + V | .6126 (.1102) | .3794 | .8229 | 90 %     |

TABLE 5: Results for direction prediction on the humorous segments, reported as AUCs. The columns are analogous to those of Table 4.

Illustrated by the maximum AUCs for audio, e.g., .7656 for Deep Spectrum.

The best mean AUCs are obtained when experimenting with textual features.

We hypothesise that the direction of an utterance is mainly encoded in its semantics and thus typically hard to predict from facial expressions or acoustic signals alone. Each textual feature outperforms all acoustic and visual features and the vast majority of textual experiments result in AUCs above chance level. Again, ELECTRA is the best performing text-based feature on average with a mean AUC of .6108. The relative aptitude of text for predicting humour direction can be explained by direction being encoded in the semantics of an utterance. Oftentimes, it can be inferred from the content of the coach’s comments whether he is joking about himself or others. Intuitively, this is typically not the case for facial expressions and paralinguistic features. However, the performance of textual features here probably suffers from the same problems already mentioned regarding textual humour recognition, namely partly highly domain-specific texts and lack of context due to not considering the interviewers’ questions.

Overall, the direction is rather hard to predict, but at least the text modality yielded some promising results. Moreover, results for direction prediction, too, are dependent on the subject, which is discussed in Section 5.2.

Because of the rather insufficient performance of audio and video features for direction prediction, they are not of much use in the late fusion experiments. Late fusion only slightly outperforms the best text-only experiment accounting for a mean AUC of .6128 for the fusion of audio and text compared to .6108 for ELECTRA only. These findings suggest that, for direction prediction, multimodal approaches may not promise significant improvements over utilising text only. They might even hurt the performance regarding those subjects that are rather hard to predict. For the trinodal fusion, the lowest AUC value observed for one of the coaches is .3794, about .0550 lower than the AUC of the worst performing coach in the ELECTRA experiments.

Hence, it can be concluded that the direction of humour is mainly encoded in the semantics of an utterance.

### 5.2.2 Sentiment

Table 6 reports the results for sentiment prediction in humorous segments.
of .7100, clearly outperforming the best visual-only (.6897) and textual-only (.6446) results. Moreover, the minimum AUC encountered for a coach increases to .6074 in the fusion of video and text, while for both video and text only, the worst performing coach only achieves an AUC of around .5500. While combining audio and video is thus beneficial, it seems like the audio modality could actually worsen the results. Fusing audio and video yields a lower mean AUC value than the FaRL experiments, with .6482 AUC compared to .6897 and also the trimodal mean AUC result is about .0100 lower than the result when only text and video are combined. We find that this phenomenon is due to massive overfitting to the training data when training SVMs using eGeMAPS features. On the training data, we find AUCs of over .9000, which causes audio-based predictions to receive larger weights than video and text-based predictions according to the algorithm described in Section 4.2.3, though the audio modality is, in comparison, the least suitable modality for sentiment prediction.

5.3 Individual Results
Motivated by the partly large standard deviations and gaps between the best and worst performing coaches’ AUCs observed in Tables 4 to 6, we analyse our results w.r.t. the individual coaches in the following. Table 7 contains the best results obtained for every single coach in each of the three tasks and for each of the three modalities. Moreover, it provides each coach’s rank per task based on the best result (across all modalities) for the respective coach.

Some coaches are generally easier to predict than others. Consider for example coaches 1 and 9. Coach 1 is ranked 3rd for both humour recognition and direction prediction and first in sentiment prediction. In contrast, coach 9 ranks last in humour recognition and sentiment prediction and second-to-last in direction prediction, indicating that our approaches struggle with modelling his type of humour. There are also coaches whose humour can be detected relatively easy but this does not transfer to the classification of sentiment and direction. For example, for coach 6, an AUC of .9593 is achieved for binary humour recognition, ranking him second in this task, while he only ranks 9th and 6th for sentiment and direction prediction, respectively. A similar phenomenon, yet reversed, can be observed for coach 10. While for humorous segments of this coach, both sentiment and direction are relatively easy to predict, ranking him 3rd and 4th, respectively, he ranks second-to-last in the binary humour detection task.

For the recognition of humour, Table 4 suggests that, for humour recognition, visual features outperform textual features which in turn lead to better results than audio features. This is confirmed by Table 7 for most cases, except coaches 1 and 9. Coach 9 is, in general, hard to predict and for humour, visual features do not work well for him, either. While for all other coaches, more than .8000 AUC can be achieved, coach 9's humour AUC with visual features is only .7083, inferior to his textual AUC value of .7266. However, this coach was found to benefit the most from late fusion, improving his AUC value to .7825 utilising all three modalities. Audio outperforms text for humour recognition in only one case, namely coach 1.

In the direction prediction task, the textual features work best for most of the coaches, consistent with the results discussed in Section 5.2.1. However, similar to the observations for sentiment prediction, there also exist a few outliers. The highest AUC values for coaches 8 and 9 are achieved using audio features, while for coach 9, the textual feature result of .5352 AUC is only slightly above chance. For coach 1, the visual modality is responsible for the best result. Coach 1 and 5 are the only coaches, for whom AUCs of over .6000 can be observed when using visual features.

As shown in Table 6, visual features typically yield higher AUCs than textual and audio features in the sentiment prediction task. In three cases, however, the text modality leads to better results than the video modality, most notably for coach 6, where both audio and text features outperform the AUC value of .5513 obtained with visual features. For the same coach, however, visual features perform well in humour detection, leading to the second best humour AUC among all coaches. Furthermore, it can be seen in Table 7 that for some coaches all modalities achieve similar results, e.g., coach 10 in sentiment prediction, while for others, there are large discrepancies between the respective best AUC values per modality, e.g., coach 1.

To summarise, while there are general tendencies as to which modality works best for which of the three tasks, the results on the individual level often deviate from such generic assumptions. This highlights the fact that humour styles differ among individuals and humour can be expressed in different ways. Hence, models trained on a set of persons do not always generalise well for a previously unseen person.

6 Conclusion
We introduced PASSAU-SFCH, a novel dataset for humour recognition that differs from existing datasets regarding the spontaneity and sparsity of the humorous utterances and its rich annotation scheme including the two dimensions of humour proposed in the HSQ.

Then, we investigated the suitability of different modalities (text, audio, and video) for the tasks of humour recognition as well as sentiment and direction classification. To do so, a rich set of features was employed. Our experiments show that humour in PASSAU-SFCH is well-predictable, in particular when using the video modality. The sentiment of humorous segments proved to be harder to predict than humour, resulting in lower AUC values than those observed for humour prediction. In sentiment prediction, the video modality, in general, led to the best results, too. Direction (self- vs other-directed) of humorous segments turned out to be the most difficult prediction target. Here, text stood out as the most promising modality. Moreover, for all three tasks, improvements via prediction-level fusion of models trained on different modalities could be noted. When analysing the results on an individual level, we find substantial differences among the coaches in terms of AUC values in general and for different modalities.

These results strongly suggest that automatic humour recognition systems would benefit from personalisation strategies. First experiments on personalising ML models trained on PASSAU-SFCH have already been conducted [97]. Further future work may include developing
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TABLE 7: Comparison of results for individual coaches (denoted by ID) for the tasks of humor recognition as well as direction and sentiment prediction. Reported are the best mean results per coach and modality. The best result per modality and task across all coaches is underlined. R denotes the rank of each coach for the three different tasks. The rank is determined by sorting the coaches according to their best mean AUC value per task.

| ID   | Audio Text Video Rank | Audio Text Video Rank | Sentiment Audio Text Video Rank |
|------|-----------------------|-----------------------|---------------------------------|
| 1    | 7763 7497 9485 3     | 6082 7424 4994 3     | 6690 6932 8153 1               |
| 2    | 8494 8827 9625 1     | 7656 8281 8854 1     | 6222 6984 8914 6               |
| 3    | 7682 8916 9451 4     | 5638 7784 4843 2     | 6835 7296 8733 2               |
| 4    | 7264 8118 8899 8     | 5342 6039 4996 10    | 5816 6527 6902 7               |
| 5    | 6991 7703 9193 6     | 6153 7040 6549 5     | 6613 7187 6748 5               |
| 6    | 7528 7843 9593 2     | 6298 6973 5069 6     | 5684 6346 5531 9               |
| 7    | 7689 8087 8997 7     | 5233 6719 5193 7     | 6153 6466 7472 4               |
| 8    | 7841 9169 9383 9     | 6688 6406 5420 8     | 5574 6764 6686 8               |
| 9    | 7036 7266 7083 10    | 6087 5352 5893 9     | 5441 5731 6321 10              |
| 10   | 7351 7442 8255 9     | 5331 7122 4697 4     | 7109 7116 7520 3               |

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