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# Toward Automated Classroom Observation: Multimodal Machine Learning to Estimate CLASS Positive Climate and Negative Climate

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**Abstract**—In this work we present a multi-modal machine learning-based system, which we call ACORN, to analyze videos of school classrooms for the Positive Climate (PC) and Negative Climate (NC) dimensions of the CLASS [1] observation protocol that is widely used in educational research. ACORN uses convolutional neural networks to analyze spectral audio features, the faces of teachers and students, and the pixels of each image frame, and then integrates this information over time using Temporal Convolutional Networks. The audiovisual ACORN's PC and NC predictions have Pearson correlations of 0.55 and 0.63 with ground-truth scores provided by expert CLASS coders on the UVA Toddler dataset (cross-validation on  $n = 300$  15-min video segments), and a purely auditory ACORN predicts PC and NC with correlations of 0.36 and 0.41 on the MET dataset (test set of  $n = 2000$  video segments). These numbers are similar to inter-coder reliability of human coders. Finally, using Graph Convolutional Networks we make early strides (AUC=0.70) toward predicting the specific moments (45-90sec clips) when the PC is particularly weak/strong. Our findings inform the design of automatic classroom observation and also more general video activity recognition and summary recognition systems.

**Index Terms**—automatic classroom observation, Classroom Assessment Scoring System, facial expression recognition, auditory analysis

## 1 INTRODUCTION

The quality of teacher-student and student-student interactions in school classrooms both predicts and impacts students' learning outcomes. Numerous correlational [2], [3], [4], [5], [6] and some large-scale causal [7], [8] studies have demonstrated the link between emotional and instructional support in the classroom and children's downstream cognitive, social, and emotional skills. In order to characterize classroom interactions precisely, educational researchers have developed a variety of classroom observation protocols. One of the most widely used protocols is the Classroom Assessment Scoring System [1] (CLASS). A typical CLASS observation session requires human annotators – who could be teachers, educational researchers, or school administrators – to examine specific characteristics of the states, actions, and interactions among the students and teachers during either live observation or recorded videos.

While CLASS coding is a valuable tool for educational research and teacher training, its utility is limited by the difficulties of manual coding: Human coding of CLASS scores requires significant training, is slow and expensive, and can suffer from significant inter-coder variability. On the other hand, the success of contemporary deep learning methods for object recognition, emotion recognition, and speech analysis, as well as multimodal methods for activity recognition and video analysis, raises the question: Could particular aspects of classroom observation be performed by a machine, and/or could automated perceptual tools assist human annotators in coding classroom videos?

**Machine learning for educational measurement:** The last ten years have seen a surge of interest in harnessing machine learning to develop new tools for educational measurement (see Related Work section below). Most of this work has focused

on analyzing individual students' engagement and emotions [9], [10], [11], [12], or classifying teachers' pedagogical actions from their speech [13]. During just the past few years, there has been increasing interest in whole-classroom analysis from video [14], [15], [16]. In this paper we build on our pilot work [15] and explore a variety of multimodal (vision, audition, language) deep learning methods to estimate CLASS Positive Climate (PC) and Negative Climate (NC) dimensions automatically from classroom videos. Such videos (see Figure 2 for an example) present numerous and severe challenges for both computer vision and audio analysis, including noisy and overlapping speech, very young children whose speech is imprecisely pronounced, extreme head pose, visual occlusion, uncontrolled lighting, and visually complicated backgrounds. Given these challenges, we identify promising architectures for low-level perception of both visual and auditory features, as well as high-level temporal integration designs to estimate CLASS scores. We dub our final system the ACORN (Automatic Classroom Observation Recognition Network), and we validate it on two CLASS-coded datasets (UVA Toddler, and MET). While the application focus of our paper is on educational measurement, our results also have implications for other affective computing, video analysis, and activity recognition problems, especially when the target variable is semantically “high-level” like in our setting.

At the onset of this research project (WPI IRB #17-151), it was unclear to us whether semantically high-level constructs as CLASS Positive Climate and Negative Climate could be estimated by a machine to any degree of accuracy. Through an iterative design process, harnessing contemporary computer vision and speech analysis techniques, and by designing new information integration architectures and training procedures, we have been able to increase accuracy steadily to match (and possibly exceed) inter-coder reliability of human CLASS coders. This paper shares

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many of the multi-modal machine learning insights we learned along the way.

### 1.1 Technical contributions and novelty

**Automated CLASS estimation:** The ACORN presented here is the first fully automated system to estimate from classroom videos the dimensions of the CLASS, and it attains an accuracy similar to that of human coders. Analyzing classroom videos is a highly challenging video activity recognition problem: In contrast to much of the prior literature on activity recognition [17], [18], [19], in which the temporal span of activities are usually just a few minutes (or even seconds) and are easy for ordinary humans to perceive (e.g., “take out from fridge”), in our setting each video segment is 15 minutes, and the perceptual task requires significant training (usually at least several weeks of practice to become competent in CLASS coding). Our ACORN can potentially serve as a scientific instrument to provide feedback to teachers and facilitate educational research. The work here significantly extends our earlier paper [15] by harnessing more powerful audiovisual perceptual architectures to achieve higher accuracy (0.55 vs. 0.40 for PC, 0.63 vs. 0.51 for NC), automatically identifying the most important moments in a classroom video, and evaluating on more and larger datasets. Our work also distinguishes itself from related systems for automated classroom analysis in several ways: We develop perceptual models for both video and audio (rather than audio alone [13]); our system estimates a high-level semantic judgment of classroom dynamics over a long time-span (rather than focusing on recognizing individual low-level behaviors [14]), and we use more complex neural networks compared to [20].

**Human activity recognition from video – what details matter?**: As an instance of human group-activity recognition research, our work provides insights, through a sequence of controlled experiments (models #1–#21 trained & tested using double classroom-wise cross-validation), into what architectural details (CNN backbone, attention, temporal integrator, theory-driven feature engineering) are important for capturing semantically high-level attributes over relatively long time-scales (15min). This kind of empirical study deepens the understanding of which accuracy improvements within a complex multi-modal machine learning system are additive, and which are subsumed by others. The trends we identify are largely consistent for both the PC and NC dimensions of the CLASS, and persist even after randomly re-shuffling the cross-validation folds.

**Graph convolution for key-event detection – importance of topology:** We develop a computer vision approach – based on graph convolution networks (GCN) [21] over a graph induced by the 2-d positions of detected faces, combined with graph attention and recurrent neural networks – to identify the most salient moments within a classroom video; this is a kind of key-event detection and video summarization task. Our results suggest that this approach delivers higher accuracy than several other methods (e.g., the recently proposed Siamese video highlighting model [22]). Moreover, we conduct novel ablation analyses on the graph topology to verify that the benefit of our GCN layer derives from *interactions* between neighboring students and teachers, not just from having another non-linear + pooling layer within a larger network.

## 2 RELATED WORK

Researchers from computer science, cognitive science, and psychology have explored how to use machine learning to perceive

students, teachers, and classrooms for over 20 years [23]. This work varies along several dimensions, including the target attribute to predict, sensors used as inputs, and algorithmic approach.

**Target attributes:** Most work in the intersection of machine perception and education has focused on automatically characterizing individual students’ affective states, including engagement [11], [24], [25], [26], concentration [27], [28], [29], frustration [25], [26], [30], and other achievement emotions [31]. This can be useful for giving teachers real-time or post-hoc feedback about how students respond to their instruction, or as a real-time reward signal to intelligent tutoring systems [12], [32], [33] or robot tutors [24]. Some researchers have investigated how to identify teachers’ behaviors and pedagogical strategies [13], [16], [34], [35]. Finally, during the past several years, a few projects have also emerged (including ours) that analyze the dynamics of an entire classroom, either as the collection of individual students [14] or an aggregate measure of many interacting participants [15], [36]. This can provide the raw data for teacher dashboards and also facilitate automated classroom observation coding.

**Sensors:** Many approaches use computer vision to analyze the facial expressions, head movements, and body posture of students [11], [14], [20], [23], [24], [25], [26], [37]; this line of research stems largely from the face and gesture recognition, multi-modal machine learning, and affective computing communities. Others analyze audio and speech [13], [16], [34], [35], which is arguably less privacy-invasive than vision, to characterize the kind of instruction used in a classroom at each moment in time. There are also “sensor-free” approaches [27], [28], [29], [38], often led by researchers in the educational data mining community, that predict students’ future behaviors or emotions by analyzing the log files generated from intelligent tutoring systems and massive open online courses. These log files typically contain a record of all the decisions that students make (e.g., open a certain module) or answers they give in response to practice questions. Finally, there are also a few studies make use of just text [31], e.g., from online discussion forums, to judge students’ emotions.

**Algorithms:** During the last several years, there has emerged an array of high-quality off-the-shelf software tools for automatic visual perception such as OpenPose [39], OpenFace [40], as well as cloud-based services for vision and speech analysis such as Amazon Rekognition and Google Cloud Speech. These systems are usually based on deep learning algorithms and are presumably trained on very large datasets to yield high accuracy. Hence, it is natural to use them as the low-level perception engines that can then be further processed to estimate higher-level attributes [13], [14], [20], [24], [25], [37]. On the other hand, such systems and services are not tailored to student learning or classroom environments, and it is possible that bespoke models that are trained specifically on the target population may work better. Hence, many researchers have trained their own custom perception systems [11], [15], [20], [34], [38].

### 2.1 Machine perception of school classrooms

Here we briefly summarize machine learning-based perceptual systems that analyze entire school classrooms. D’Mello et al. [35], [41] explored how to segment and recognize students’ and teachers’ speech in unconstrained classrooms based on different microphone configurations. Wang et al. [42] segmented teachers’ speech by deploying small wearable recording devices in math classrooms. Ahuja, et al. [14] developed a combined hardware

and software toolkit called EduSense that detects students' body and facial movements automatically. Their system uses OpenPose [39], as well as multiple classifiers (random forests, support vector machines, multi-layer perceptrons) trained on top of its outputs, to track each student in each video frame as well as their body posture, hand gestures, and facial expressions. It also analyzes audio features recorded from different microphones to determine whether speech was produced by students versus the instructors. The machine learning architecture in [16] is based on an ensemble of decision trees that analyze the volume and standard deviation of classroom sound in 15sec intervals, where the goal is to classify different classroom activities.

Due to its popularity in educational research, recently some computational researchers have developed methods to automate aspects of the Classroom Assessment Scoring System (CLASS). The earliest work in this vein was by Qiao and Beling [36], who developed a computer vision system, optimized within a multiple-instance learning framework, to estimate which 3-minute clips within classroom videos were most relevant for CLASS coders to code manually. Note that 3 minutes is significantly shorter than the 15-20min annotation interval that is prescribed by the CLASS manual (see Section 3); this is because their system was designed to identify the key moments that warranted closer human inspection, rather than to estimate CLASS scores themselves. James et al. [37], [43] pursued an architecture similar to our prior work [15] for automatic recognition of CLASS climate scores. However, in contrast to the CLASS definition, which defines Positive Climate and Negative Climate as independent dimensions, their work treats these as two sides of a spectrum. [15] explored BiLSTMs that analyze facial expression features as well as CNNs that analyze low-level audio features. Compared to [15], the present work explores more powerful architectures and uses a larger dataset to achieve substantially higher CLASS prediction accuracy.

### 3 CLASSROOM ASSESSMENT SCORING SYSTEM

The Classroom Assessment Scoring System (CLASS) [1] is a validated and widely used [44] observation protocol to measure the quality of teaching in school classrooms. When performing CLASS coding, human observers analyze the classroom interactions between teachers and students, and between students and their peers, along 8-12 (the number varies depending on the age group) *dimensions* that are partitioned into 2-4 *domains*. For example, for toddler classrooms, there are two domains: (1) Emotional and Behavioral Support, with 5 dimensions: Positive Climate, Negative Climate, Teacher Sensitivity, Regard for Child Perspectives, and Behavior Guidance; and (2) Engaged Support for Learning, with 3 dimensions: Facilitation of Learning and Development, Quality of Feedback, and Language Modeling. A single score on a 1-7 integer scale is assigned to each dimension based on observing a 15-minute portion of classroom instruction. CLASS scores from expert human coders have shown to predict a variety of downstream educational and socio-behavioral outcomes [2], [3], [4], [44].

Within the *emotional support* domain of the CLASS, two dimensions are the **Positive Climate (PC)** that measures the "warmth, respect, and enjoyment communicated by verbal and nonverbal interactions" between students and teachers; and the **Negative Climate (NC)** that measures the "overall level of ex-

Positive Climate	
Indicators	Behavioral Markers
Relationships	Physical proximity, matched affect
Positive Affect	Smiling, laughter, appropriate praise
Respect	Eye contact, warm voice, supportive language

Negative Climate	
Indicators	Behavioral Markers
Negative Affect	Irritability, harsh voice, anger
Punitive Control	Yelling, threats
Teacher Negativity	Sarcastic voice, humiliation
Child Negativity	Victimization, bullying

TABLE 1: The CLASS Positive and Negative Climate as presented in [1]. Each Climate is sub-defined in terms of indicators, each of which has multiple behavioral markers.

pressed negativity in the classroom" [1]. The focus of our paper is on recognizing these two dimensions automatically.

#### 3.1 Coding Guidelines

The CLASS manual for each age group (toddlers, kindergarten, elementary school, etc.) provides guidelines for how to score each dimension. Scores are typically assigned for each dimension once every 15 minutes (and sometimes up to 20 minutes [45]); this timescale allows enough time for meaningful judgments about the quality of classroom interactions to be made. Each judgment is based on the presence or absence of *behavioral markers* that belong to a specific *indicator* of a particular CLASS dimension; in this sense, CLASS is organized hierarchically. The behavioral markers can span auditory, visual, linguistic, and pedagogical dimensions. For example, when assessing Positive Climate, CLASS coders are instructed to consider how frequently smiles are exhibited by classroom participants; whether the teacher calls his/her children by name and looks them in the eye; whether the emotions between teachers and students are congruent; etc. Negative Climate can be signified when a teacher raises his/her voice in anger at a student; makes threats to punish them if they do not behave; etc. While these specific behaviors can serve as anchor-points for coding, the CLASS score for each dimension is a holistic judgment based on the entire 15-min video segment. Table 1 shows a small subset of the behavioral markers to which CLASS coders should attend for Positive Climate and Negative Climate. Importantly, Negative Climate is not just the absence of Positive Climate. Rather, the former is characterized by the presence of overt negative behavior such as threats and punitive control. A classroom with low Positive Climate can thus also have low Negative Climate.

To become proficient in CLASS coding, human observers typically enroll in a multi-day training seminar and then continue to practice and receive feedback over the course of several weeks or months. Proficiency is certified by an online exam. Once trained, CLASS coders can watch either live or videorecorded classroom sessions and provide a valuable service for teachers, administrators, and researchers. However, the amount of time involved in CLASS coding is significant and the work is expensive.

### 4 MULTIMODAL MACHINE LEARNING APPROACH

Our design philosophy when designing the Automatic Classroom Observation Recognition Network (ACORN) was to combine hand-selected features as suggested by the CLASS Manual (e.g., affective states of classroom participants as estimated from their

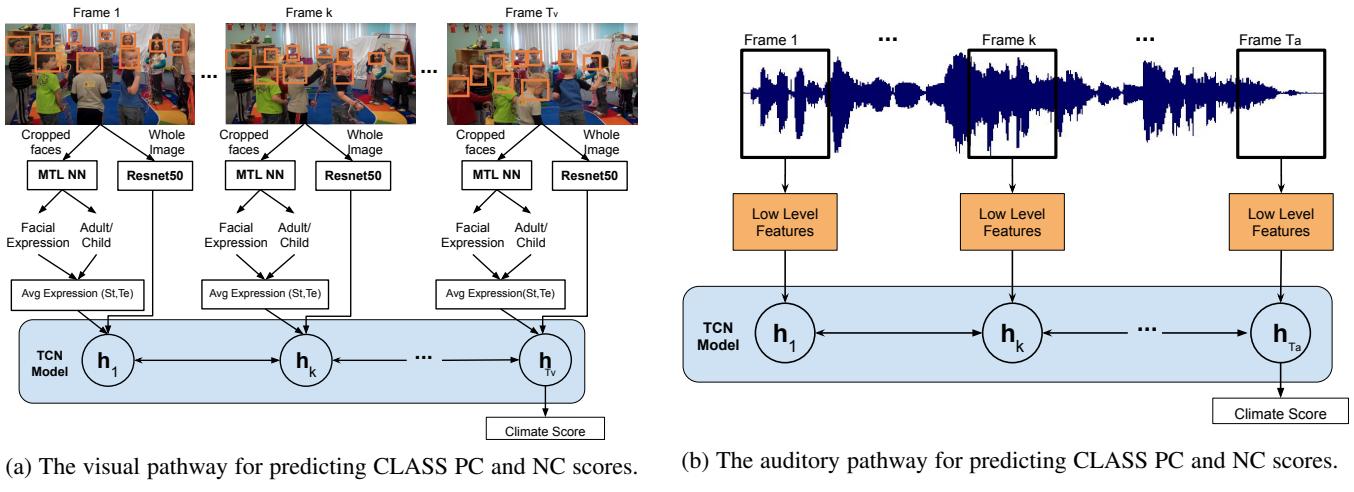


Fig. 1: Automatic Classroom Observation Recognition Network (ACORN) comprising a visual and an auditory pathway whose outputs are averaged together to estimate CLASS scores.

facial expressions) with low-level auditory and visual features such as raw pixels and MFCC coefficients that are analyzed by convolutional neural networks. We treated CLASS score estimation as a multi-classification rather than a regression problem (see discussion in the Supplementary Materials) so that the system outputs one element from the set  $\{1, 2, \dots, 7\}$ , as prescribed by the CLASS Manual.

This paper explores and estimates the predictive power of visual and auditory feature representations for predicting CLASS PC and NC. We also assess the accuracy of different approaches to integrating information over time.

#### 4.1 Visual features

There are a variety of visual behavioral markers that suggest Positive Climate. For instance, positive affect is signaled to some extent by *facial expressions* such as smile, and positive relationships are associated with *congruent* facial expression between the teacher and her/his students, i.e., the teacher shows positive emotion when the students show positive emotion. Similarly, overt displays of anger, frustration, or sarcasm indicate negative climate. Finally, we also consider that important classroom events and interactions might be identified by a convolutional neural network that analyzes the *whole image* of each video frame. To avoid overfitting, especially when analyzing the pixels of the video frames, we used CNNs that were pre-trained on ImageNet.

#### 4.2 Auditory features

Classroom speech is clearly a crucial factor for all CLASS dimensions, including PC and NC. Analogously to estimating emotion by facial expression from video, we train automatic emotion detectors from audio and use them to estimate PC and NC. Also, analogously to analyzing all the pixels of every video frame, we also extract *low-level audio features* (e.g., MFCC representation) of the classroom audio that may capture paralinguistic and prosodic features such as sarcasm, laughter, yelling, screaming, crying, etc.

#### 4.3 Temporal Integration

Given a time series of features (e.g., CNN-based features of the pixels of each video frame, facial expression of teachers and

students at each moment in time, utterances of key phrases, etc.), we must analyze this time series to arrive at a final estimate for the CLASS scores. We explore several approaches: Most simply, we can simply compute the *average* over the whole time series (15 minutes in our datasets). We can use *recurrent neural networks* such as LSTMs and bidirectional LSTMs. More recently, [46] showed that a *temporal convolution network* (TCN) introduced in [47] could outperform LSTMs in terms of speed while also demonstrating a longer effective memory.

#### 4.4 Overview of experiments

In the sections below, we describe our experiments to investigate the most effective methods of temporal integration (e.g., BiLSTM, TCN), feature representation (e.g., multiple facial expressions, pixels of whole video frame), and neural network architectures (e.g., attention, graph convolution). For CLASS PC and NC score estimation, Sections 6 (audio), 7 (video), and 8 (ensemble) analyze the UVA Toddler dataset, whereas Section 10 examines the much larger MET dataset and explores how model accuracy varies as training set size increases. For finding the key moments within a 15min classroom video with high vs. low PC, the experiments in Section 11 are conducted on the UVA Toddler dataset.

Note that we did not try all possible combinations of all features, neural network designs, and temporal integration methods, as this would result in a very large number of experiments. Instead, we followed an iterative development approach whereby the most promising architecture we had identified so far was modified slightly (e.g., inclusion of a neural attention model) to see if the new component made a difference. The design of our final ACORN system is shown in Figure 1 that represents both the visual and auditory pathways whose votes for the CLASS scores are averaged together.

#### 5 DATASETS

We trained and tested our models on two CLASS-coded datasets: the University of Virginia (UVA) Toddler dataset, which contains pre-school classrooms of young children (2-3 years old), and the Measures of Effective Teaching (MET) hosted at the University of Michigan, which contains middle-school classrooms (typically



Fig. 2: Example settings of classroom as present in the UVA dataset. Images shown with permission.

ages 10-14). Both of these datasets were collected in real schools in natural settings; they are not from laboratory studies.

## 5.1 UVA Toddler

The University of Virginia (UVA) Toddler dataset [48] consists of 192 CLASS-coded videos (see Figure 2), 45-60 min long, from 61 early childhood care centers, where the students are toddlers 2-3 years old. (Note that this dataset is an expanded version of the one we analyzed in our prior work [15].) UVA Toddler was collected as part of an Institute for Educational Sciences (IES)-funded study to explore new professional development models for teachers. Videos were recorded by a trained observer (either a teacher or videographer) using a tripod-mounted digital camera with integrated microphone, with the goal of visually following the most interesting aspects of the classroom dynamics at each moment in time. Each video shows classroom footage from a typical day of pre-school instruction, including individual activities, group activities, outdoor play, and shared meals (see Figure 2). Pre-school classrooms often include singing, reading activities led by the teacher, playing with blocks and other toys, and eating breakfast. In most classrooms, at least two caretakers (teachers and aides) are present: averaged over all videos, there are 1.70 teachers (s.d. 0.787) and 7.59 students (s.d. 2.22) per classroom session. As shown in the figure, classroom observation videos are highly challenging for computer vision systems due to uncontrolled lighting and highly non-frontal head and body pose of the participants; overlapping speech and noisy backgrounds contribute to the difficulty of auditory analysis as well.

### 5.1.1 Demographics

All teachers were female. Race of teachers: Black/African American (48.2%), White/Caucasian (39.3%), Asian (3.6%), multiracial (3.6%), and other (3.6%). Ethnicity: 1.8% of teachers reported being Hispanic. All videos were recorded from classrooms in a Mid-Atlantic state of the USA.

### 5.1.2 CLASS Coding

In accordance with the coding guidelines described by the official CLASS Manual [1], each video is split into 15-minute segments,

and each segment is labeled for the 10 dimensions of the CLASS-Toddler protocol. In total this amounts to 300 15-minute video segments distributed across the 7 classes as shown in Table 2. This size is comparable to recent affective computing and classroom analysis studies [20], [49]. CLASS coding was performed by 9 coders, who underwent 2 days of training for the CLASS-Toddler protocol and completed a reliability assessment prior to coding.

A random sample of about 10% of the video segments were labeled by multiple CLASS coders to assess inter-coder reliability; see the confusion matrix in Table 5 (bottom). Also, between the PC and NC dimensions for these videos, the Pearson correlation was  $-0.446$ , i.e., videos with higher PC tended to have lower NC.

Dimension	CLASS Score						
	1	2	3	4	5	6	7
Positive Climate	0	7	28	74	78	92	21
Negative Climate	243	43	11	3	0	0	0

TABLE 2: # labeled video segments for each CLASS score in the UVA Toddler Dataset.

For training our models, we treat each label from each coder as a distinct example; this approach has been shown in some prior studies to boost accuracy compared to training on the mean label for each example [50], [51]. For evaluation, we use the mean CLASS score, over all labelers, as the ground-truth.

## 5.2 MET Elementary and Middle School

The Measures of Effective Teaching (MET) dataset [8] is one of the largest CLASS-coded video datasets ever collected. It contains over 16000 videos from 3000 teachers teaching mathematics, science, or language arts classes in elementary and middle schools in 6 districts across the USA. In each classroom, a 360-degree spherical camera with integrated microphone was placed in the center of the room and used to record both the teacher and students simultaneously. MET was collected by the Bill & Melinda Gates Foundation and is hosted by University of Michigan. Videos are accessible only from inside the Virtual Data Enclave (VDE), which is a set of virtual machines that provide restricted access to the data. No data transfer is possible into or out of the VDE without explicit authorization from the University of Michigan. All analyses must be conducted in approved software.

### 5.2.1 Demographics

Averaged over all 6 school districts in the study (weighted by the number of participants from each district), the demographics [52] of teachers were as follows: 77.8% female, with 24.7% African-American, 9.1% Latino/Latina, 62.8% non-Hispanic White, and 3.4% other Race or Ethnicity. Demographics of students: 48.7% female, with 30.4% African-American, 33.9% Latino/Latina; for the remaining students, race and ethnicity data was missing.

### 5.2.2 CLASS Coding

The histogram of PC and NC scores is shown in Table 3. Like UVA Toddler, the MET dataset has been scored by multiple (71) unique coders for all the CLASS dimensions. The inter-coder confusion matrix is shown in Table 6 (bottom). Between the PC and NC dimensions, the Pearson correlation was  $-0.335$ .

Dimension	CLASS Score						
	1	2	3	4	5	6	7
Positive Climate	23	271	883	1458	1632	1037	270
Negative Climate	3727	1385	323	80	31	21	7

TABLE 3: # labeled video segments for each CLASS score in the MET Dataset.

## 6 EXPERIMENTS: AUDITORY PATHWAY

We first consider prediction architectures that use only auditory features. This approach has a possible advantage in terms of privacy: some students and teachers may feel more comfortable with their voices being recorded than videos with their faces. Auditory features may be predictive of CLASS PC and NC in various ways: At a gestalt level, they may give a sense of how much excitement or activity is taking place in the classroom. At a finer-grained level, the audio records who said what to whom and when, and with what emotion. Here we use spectral features such as MFCC and Chroma.

The experiments in this section, which are all conducted on the UVA Toddler dataset, investigate which temporal integration mechanism (simple average, 1-D CNN, BiLSTM, TCN) is most effective for aggregating audio information for CLASS estimation.

### 6.1 Procedures

Our models were trained with Adam using an initial learning rate of 0.001 with annealing, for 500 epochs, with early stopping patience of 25 epochs. We trained and evaluated our models on the UVA Toddler dataset using 10-fold classroom-wise cross-validation, subject to the following stratification constraints: (1) Whenever possible, all climate levels (1-7) were represented in each fold; and (2) No two folds contained a video clip from the same classroom. We further subdivided each training fold (i.e., double cross-validation) into two subsets: one for parameter optimization (training) and one for hyperparameter optimization (validation). Just before submitting the paper, we *re-sampled* all the cross-validation folds and re-ran *all* the experiments to ensure that our findings were robust w.r.t. the particular choice of folds. Almost all the trends we found regarding *which model worked better than others* remained the same; we report only those trends that remained consistent after reshuffling folds.

We trained our neural networks to estimate a probability distribution over 7 discrete outputs  $\{1, 2, \dots, 7\}$  using cross-entropy loss. We then treated the predicted class label as a real number and computed the Pearson correlation with ground-truth human-coded ordinal CLASS scores, similarly to how facial expression intensity estimation has been evaluated in past studies [53]. For statistical significance testing, we compute 2-tailed t-tests that the mean of the correlations across all 10 folds is different than 0. We report correlation results in the body text below, and most of them are also shown in Table 4. Beside each “Results” heading below, we report the corresponding model # in the table.

### 6.2 Low-Level Auditory Features

We extracted all the 34 features available from the PyAudioAnalysis toolkit [54]. Each audio file is first partitioned into non-overlapping windows of length 50ms (and thus the sampling rate of windows is 20Hz); each of these is then further partitioned into two sub-windows of length 25ms. Features are computed within

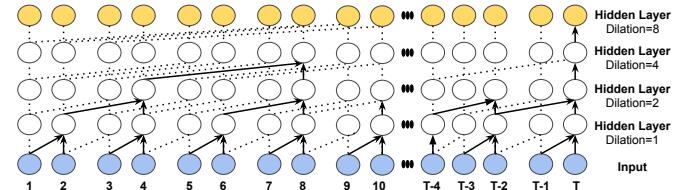


Fig. 3: Temporal Convolutional Network (TCN) [47] with dilation strides of 1,2,4,8.

each subwindow and then averaged over the two subwindows; this is the approach suggested by [54]. Thus, for a 15min (900sec) audio, there are 18,000 vectors containing 34 features such as Mel Frequency Cepstral Coefficients (MFCC), Chroma features, and various other spectral features. Given these features, we compared several temporal integration methods, described below.

#### 6.2.1 Simple Average

Early during the development of ACORN, we wanted to explore if there was any correlation between the average audio features across each video and the corresponding CLASS PC and NC scores. We thus trained two decision trees (one each for PC and NC) using the CART algorithm [55] that took the 34-dimensional average audio feature vector as input and predicted the CLASS score. Note that decision trees can capture non-linear relationships.

**Results (model #1):** PC and NC were predicted with Pearson correlations of 0.27 and 0.26 w.r.t. ground-truth scores, respectively; both were statistically significant. These provide evidence that low-level audio features, even without downstream speech recognition or NLP, can be useful for CLASS prediction.

#### 6.2.2 1D Convolution Approach

As a more powerful feature representation than just the mean audio feature vector, we trained a 1-D CNN that analyzes the 18,000 audio vectors over the whole video by applying fixed-length temporal kernels. In particular, the network consisted of a 1-D convolutional layer (128 output channels, kernel width of 10 timesteps), followed by a ReLU activation function, global average-pooling over the time axis, and finally a dense layer combined with softmax to estimate the CLASS score.

**Results (model #2):** PC and NC were predicted with correlations of 0.28 and 0.26, respectively; both were statistically significant.

#### 6.2.3 BiLSTM

To capture not just average local behavior but also the dynamics of the audio time series, we applied recurrent neural networks. In particular, we trained a BiLSTM with 1 hidden layer containing 100 neurons that takes each 34-dim audio feature as input and produces a CLASS score estimate at the final timestep.

**Results (model #3):** PC and NC were predicted with correlations of 0.23 and 0.22, respectively; both were statistically significant. These correlations are actually lower than both the Simple Average and the 1D-CNN. This might be due to vanishing gradients from the large number of timesteps.

#### 6.2.4 Temporal Convolutional Network

Simple 1-D CNNs can be seen as a special case of the more powerful Temporal Convolution Network (TCN). Figure 3 shows a TCN with a single residual block with dilation strides of

$\{1, 2, 4, 8\}$ . Through stacking dilated convolution layers, the TCN can have a very large receptive field with relatively few layers and thus maintain computational efficiency. TCN are an alternative to LSTM and GRU networks and can retain high accuracy while reducing run-time costs. We thus tried using a TCN to predict CLASS scores from the audio feature. The TCN took a 34-dim audio feature vector at each timestep and produces a single CLASS score estimate as output in the final timestep.

**Results (model #4):** PC and NC were predicted with correlations of 0.29 and 0.33, respectively; both were statistically significant. This is a modest improvement in accuracy over the Mean+DT, 1D-CNN, BiLSTM models. One explanation is that the auditory *dynamics*, rather than just local behavior or global average behavior, are predictive of PC and NC. An alternative explanation is that increasing the computational depth beyond just a single convolutional layer may transform the local signals to be more predictive.

### 6.3 Additional Experiments

The Supplementary Materials contain additional experimental results on using key-phrase classification from a custom-trained neural network [56], pre-trained audio event detection networks, auditory emotion classification, and speech-to-text transcription using DeepSpeech [57], [58]. These results are not statistically significant. Our previous work [15] also includes experiments to explore how to handle data imbalance, which we omit here for brevity.

## 7 EXPERIMENTS: VISUAL PATHWAY

Here we explore prediction architectures for CLASS PC and NC that use purely visual features of facial expression and the number of detected faces in each frame. We vary aspects of the architecture such as the convolutional neural network (CNN) backbone for recognition (VGG-16 vs. Resnet-50), whether students and teachers are agglomerated or treated separately, and the temporal integration method. Experiments are conducted on the UVA Toddler dataset.

### 7.1 Facial Expression

Building on our prior work [15], we explored whether the facial expressions of students and teachers, as estimated by automatic face classifiers and integrated over time, might predict CLASS PC and NC. To this end, we trained binary classifiers of smile/non-smile, anger/non-anger, and sadness/non-sadness, as well as a child-vs.-adult detector to distinguish between students and teachers in the classroom. As reported in [15], we trained the smile and child/adult detectors on the YouTube classroom dataset we collected, and the anger and sadness on the AffectNet [59] dataset. As the first processing step, each video was split into frames at a frame rate  $f_v$  of 3Hz. Each frame was then analyzed by the Faster R-CNN face detector [60], which is robust to non-frontal faces.

In terms of binary classification accuracy of smile/non-smile and child/adult, we found that Resnet-50 as the CNN backbone gave a small but worthwhile boost in accuracy compared to VGG-16: On the YouTube dataset we collected containing 70 videos of pre-school classrooms [15], the Resnet-based classifiers achieved an Area Under the Receiver Operating Characteristics Curve (AUC) of 0.967 (versus 0.942 for VGG) and 0.90 (versus 0.879 for VGG) for child/adult and smile/non-smile, respectively.

The Resnet-based model achieved AUC scores of 0.872, and 0.884 for the tasks of sadness/non-sadness, and anger/non-anger. We thus investigated whether this accuracy boost for low-level face perception translated into a similar boost in downstream CLASS score prediction accuracy. Note: this section examines only smile, not the other facial expressions; in Section 8 we use all three expressions for CLASS prediction. We compared several approaches to temporal integration, described below.

#### 7.1.1 Simple Average

Since smiles and laughter are some of the behavioral indicators of Positive Climate, it seemed plausible that the *average* smile, across all participants and all frames of the video, might be predictive. To explore this, we trained a decision tree (using the CART algorithm [55]) that took as input the average over all frames, of the average smile estimate of every detected face within each frame, and predicted the CLASS score.

**Results (model #5):** PC and NC were predicted with correlations of 0.11 and 0.08, respectively; neither was statistically significant.

#### 7.1.2 LSTMs

To explore whether the dynamics, rather than just the average, smile values might be predictive, we computed the average smile scores within each video frame, and then passed these scores to an LSTM with 1 hidden layer containing 100 hidden units. The number of recurrent steps was 2700 (900sec for a 15-min video segment at 3 frames/second). At the end of the time series, a single output was predicted which is the CLASS score.

When computing the smile value within each frame, we compared four strategies: (1) The average smile of *all* participants (teachers and students mixed together); (2) the average smile of just the students (i.e., we use the smile scores of only those faces that are considered “child” by the child/adult detector); (3) the average smile of just the teachers; (4) the average smile of students and teachers *separately* (i.e., as two different input features). In addition, we compared VGG-16 to Resnet-50 as the CNN backbone.

**Results (models #6-#9):** Over the four different ways of computing the average smile value as described above, the most promising method was to compute the average teacher smile and average student smile separately, and then integrate these values over time with an LSTM. This method achieved a correlation of 0.13 for PC and 0.14 for NC; these results were statistically significant. Using just teacher smile or student smile (but not both) delivered lower accuracy, as did simply merging all people together. Also, nearly all the LSTM-based results were higher than model #5, suggesting that the *dynamics* of the smile was more predictive than just the mean smile value over all frames.

#### 7.1.3 BiLSTMs

Since there is usually no constraint to estimate CLASS scores in real time, we tried using BiLSTMs, which can harness knowledge of future events to understand the context of current events. As before, we compared VGG to Resnet.

**Results (models #10-11):** Analyzing the video from both directions gave a small accuracy boost compared to model #9, yielding improved stat. sig. correlations of 0.19 and 0.21 with PC and NC. Also, we found that Resnet was slightly more accurate than VGG, delivering stat. sig. correlations of 0.21 and 0.23; this suggests that the accuracy boost on facial expression recognition

(Section 7.1) can translate into modest increased downstream CLASS prediction accuracy.

## 7.2 Number of Detected Faces

In pilot exploration, we hypothesized that a very simple feature consisting of the average number of detected faces in each video frame might predict CLASS scores. The intuition is that teachers might be less effective when they must attend to many people at once. Hence, we fed a time series, consisting of the number of detected faces in each frame, to a BiLSTM and predicted PC and NC with this sole feature.

**Results (model #12):** There was a weak correlation of #faces with PC and NC: 0.07 and 0.09, respectively; neither was statistically significant. These numbers are actually higher than for model #5 (based on average smile). Since we must detect faces anyhow to compute the facial expression features, we decided to keep the #faces feature in our final ACORN.

## 8 EXPERIMENTS: ENSEMBLE MODELS

As a next step toward building the ACORN, we combined both the auditory and visual pathways. In particular, each pathway was trained independently to produce an independent estimate of the CLASS score, and the ensemble model computes the unweighted mean of these models' predictions. (In pilot experimentation, we found that learning weights over the two pathways provided no reliable benefit.) We explore factors such as the inclusion of more facial expressions, the whole image frame, and a neural attention model. The analyses in this section are conducted on UVA Toddler.

### 8.1 Smile and Spectral Audio Features

We assessed how much accuracy improves if we combine (1) an auditory model that predicts CLASS scores with a 1D-CNN from spectral audio features (model #2) and (2) a visual model consisting of a BiLSTM on top of a VGG that classifies teachers' and students' smiles separately (model #10). This has important practical implications: if the auditory model is nearly as good as the ensemble model, then it might be sensible, from a privacy perspective, to eliminate the visual pathway altogether.

**Results (model #13):** The combined approach yields correlations with PC and NC of 0.35 and 0.39; both were statistically significant. These numbers are a substantial improvement on just the visual (0.19 and 0.21) and auditory (0.28 and 0.26) models by themselves, indicating that these two pathways are highly complementary. In particular, the visual pathway contains valuable information not predicted from our auditory pathway.

### 8.2 Number of Detected Faces

Similar to Section 7.2, we tried adding the number of detected faces as an input, for each video frame, to the BiLSTM.

**Results (model #14):** Including this feature increased the correlations very slightly (w.r.t. model #13) to 0.35 and 0.40.

### 8.3 More facial expressions

In addition to the estimated smile (Sm) of each student and teacher, we investigated whether also using anger (A) and sadness (Sa) detectors might increase prediction accuracy. These two negative emotions might be particularly useful for Negative Climate. Within each video frame, we computed the average expression

value, using the appropriate binary face classifier, for teachers and students separately.

**Results (model #15):** The inclusion of anger and sadness increased the correlations (w.r.t. model #14) to 0.39 and 0.46. This suggests that richer facial emotion representations can boost accuracy in classroom observation analysis.

### 8.4 Whole-Image Analysis

Besides analyzing each classroom participant's face, other visual features that answer questions such as "where is everyone", "what are they doing" and "what are their relationships with each other" may also be important for estimating CLASS PC and NC. Hence, we investigated whether including the pixels of the entire image frame could improve recognition accuracy. In particular, we used a VGG-16 (pre-trained on ImageNet and then fine-tuned on the UVA Toddler dataset) to map each input image into a feature vector with  $7 \times 7 \times 512 = 25088$  dimensions. This vector was then concatenated with the facial expression features and #faces and passed to the BiLSTM for CLASS score estimation; hence, the whole-image and facial expression features were used jointly during training to estimate CLASS scores.

**Results (model #16):** Including the pixels of each video frame increased the correlations substantially (w.r.t. model #15) to 0.47 and 0.53. This suggests that there is substantial visual information beyond the faces that can be effectively harnessed by modern CNNs for CLASS score prediction. It is remarkable that a CNN can extract from the raw pixels a semantically high-level construct as CLASS scores.

### 8.5 Attention Models

Over the last few years, neural attention models have significantly improved the accuracy of neural networks, not just for sequential analysis tasks such as translation [61], but also in computer vision tasks [62], [63]. Self-attention mechanisms enable a neural network to attend to the most important parts of a given input, in a way loosely motivated by human visual processing [64]. In our work, we implement a variation of the self-attention as presented in [65] that we added to the Resnet-50 and VGG-16 models before the final flatten/pooling layer. To compute the attention weights we perform the following computation:

$$\mathbf{a} = \sigma(\mathbf{W}_a \mathbf{h}) \quad (1)$$

$$\mathbf{o} = \text{softmax}(\mathbf{a}) \odot \mathbf{h} \quad (2)$$

Given the output of convolution layer  $\mathbf{h}$  we first compute the self-attention output  $\mathbf{a}$  using learned attention weights  $\mathbf{W}_a$  (Equation 1). We apply a sigmoid to squeeze the outputs of  $\mathbf{W}_a \mathbf{h}$  into  $(0, 1)$ ; this helps to prevent any single feature from dominating too much over other features. Then, we apply a softmax over the attention outputs  $\mathbf{a}$  and then multiply with the original feature map itself to obtain the final attended output  $\mathbf{o}$ .

**Results (model #17):** Incorporating the attention model increased the correlations (w.r.t. model #16) to 0.51 and 0.58.

### 8.6 Temporal Convolutional Networks

Similar to Section 6.2.4, here we investigated whether using a TCN for both the auditory and the visual pathways would improve accuracy compared to a BiLSTM.

**Results (model #18):** With the TCN, the correlations were slightly worse compared to the BiLSTM approach (model #17):

0.50 and 0.56. However, the TCN is significantly faster at training and test time than the BiLSTM: Training a BiLSTM model takes about 9 hours on a P100 GPU, whereas a TCN model takes only 6 hours. At test time, for just the temporal integration (not counting the Resnet analysis of the image frame or the faces), the BiLSTM takes about 8-9 minutes per 15min video, whereas TCN takes about 3 minutes.

## 8.7 Resnet vs. VGG

Due to the improved accuracy reported for facial expression recognition in Section 7.1, we replaced VGG with Resnet to see if it increased the correlations with the ground-truth CLASS scores.

**Results (model #21):** Using Resnet as the CNN backbone increased the correlations (w.r.t. model #18) to 0.55 and 0.63.

## 8.8 Comparison with Previous Work [37]

The only prior work (besides our own [15]) of which we are aware on automatic CLASS score prediction is by James et al. [37]. Rather than adhering to the CLASS definition of detecting Positive Climate and Negative Climate as independent outputs, they treat these as two sides of a continuum and try to distinguish between positive versus negative climate over a 15-min video. We report the performance of our model by thresholding our model for PC at a score of 4. Using this threshold, the F1 score of our model is 0.86 on the UVA Toddler dataset, compared to 0.78 in [37] on their own dataset. We note that this comparison is not apples-to-apples due to a different problem formulation and testing dataset.

## 9 ACORN: COMPARISON TO HUMAN CODERS

We chose model #21 as our final ACORN. How accurate is this network compared to the ground-truth CLASS scores on the UVA Toddler dataset (defined as the average score across all human CLASS coders who labeled each example), not just at an aggregate level but broken down by CLASS score (1-7)? Does the machine make similar mistakes as human coders?

### 9.1 Aggregate

Using the 20% of the UVA Toddler dataset that was scored by multiple CLASS coders, we estimated the inter-coder reliability by taking each coder  $c$  as the ground-truth coder, computing the Pearson correlation of the other coders' scores w.r.t. the scores of  $c$ , and then averaging over all  $c$ . This resulted in an average Pearson correlation of 0.38 for PC and 0.44 for NC. (The corresponding Spearman correlations were slightly higher at 0.44 and 0.49). The accuracy of ACORN w.r.t. human CLASS codes on this dataset is, surprisingly, higher than the inter-coder reliability.

### 9.2 Confusion Matrices

Table 5 shows the confusion matrix of ACORN's predictions (rows) w.r.t. ground-truth PC and NC scores (columns) as annotated by expert CLASS coders. The tables were computed by concatenating the machine's 7-way predictions across all 10 cross-validation folds (300 predictions in total) and then normalizing within each ground-truth score. They represent the conditional probability distributions  $P(\hat{y} | y)$ , where  $\hat{y}$  is the machine's estimate and  $y$  is the ground-truth. For comparison, we also computed the inter-coder confusion matrices of human CLASS coders on the 20% subset that was multiply coded. We treated

each coder  $c$  as the ground-truth and each other coder  $c'$  as an estimator; we then averaged over all  $c$  and normalized within each column.

**Results:** Comparing the two tables for PC and the two tables for NC, we see evidence that the machine sometimes makes large errors – i.e., a large absolute difference between  $y$  and  $\hat{y}$  – that human coders do not make. For instance, for PC, the machine sometimes confused a PC score of 2 with 6. On the other hand, there were also instances of large discrepancy between human coders, e.g., the variance over the distributions  $P(\hat{y} | y = 3)$  for both PC and NC were large for human coders. There is no obvious pattern of mislabeling that the machine had that human coders did not.

## 9.3 Additional Experiments

The Supplementary Materials contain an additional analysis comparing classification- to regression-based approaches to CLASS score estimation and how this influences the empirical correlation between estimated PC and NC scores.

## 10 RESULTS ON MET DATASET

All the results so far were obtained on the UVA Toddler dataset. Does the high-level approach generalize to other populations of older students where the kinds of interactions, pedagogies, and classroom styles are very different from that of pre-school classrooms. To explore this question, we trained and tested CLASS prediction models on the Measures of Effective Teaching (MET) dataset.

Given that MET contains thousands of videos, we investigated two main questions: (1) How does the prediction accuracy (as measured by Pearson correlation) increase with the amount of training data and the model complexity? (2) How does the accuracy of the model trained and tested on elementary & middle school students compare to an analogous model trained and tested on toddlers?

### 10.1 Procedures

From the over 16000 total video segments in the MET, 5574 of them are coded for the CLASS. We split these video segments into 3874 training segments and 2000 test segments. Due to RAM constraints in the VDE which prevented us from training a single model on all 3874 segments, we again split the 3874 training segments into 10 different folds. Due to the software restrictions in the VDE, we were not able to install the necessary libraries to conduct computer vision on this dataset. Instead, we implemented only an auditory pathway: Using the tuneR audio analysis package [66], we extracted the top 200 MFCC features with the largest energies over each 1sec window at a frequency of 1Hz from each video. Using these features, we then trained random forests of  $n$  decision trees ( $n$  is a hyperparameter) to predict CLASS scores.

For each  $k = 2, \dots, 10$ , we trained random forests on  $k - 1$  folds, tested on the remaining fold as a hold-out set, and averaged results over the  $k$  folds. (Note  $k$  is *not* the number of sets into which we partition the training set like in normal cross-validation; rather,  $k - 1$  is the number of folds used for training.) We performed this process for each number of folds  $k$  and each number of decision trees  $n \in \{10, 15, 20, \dots, 50\}$ . We then picked the best  $(n, k)$  combination and trained a final model, which we evaluated on the 2000 video segments in the test set that were never seen during training or hyperparameter optimization.

#	CLASS Score Estimation Approach							Positive Climate		Negative Climate	
	Auditory Pathway		Visual Pathway					r	p	r	p
	Temp. Int..	Expressions	#Faces?	Frame?	CNN	Attn.?	Temp. Int.				
1	Mean+DT	—	—	—	—	—	—	0.27	0.002	0.26	0.003
2	1D-CNN	—	—	—	—	—	—	0.28	<0.001	0.26	<0.001
3	BiLSTM	—	—	—	—	—	—	0.23	0.004	0.22	0.009
4	TCN	—	—	—	—	—	—	0.29	<0.001	0.33	<0.001
5	—	$\{\text{Sm}\} \times \{\text{All}\}$	No	No	VGG	No	Mean+DT	0.11	0.162	0.08	0.192
6	—	$\{\text{Sm}\} \times \{\text{All}\}$	No	No	VGG	No	LSTM	0.10	0.113	0.13	0.091
7	—	$\{\text{Sm}\} \times \{\text{St}\}$	No	No	VGG	No	LSTM	0.09	0.121	0.10	0.119
8	—	$\{\text{Sm}\} \times \{\text{Te}\}$	No	No	VGG	No	LSTM	0.03	0.511	0.06	0.291
9	—	$\{\text{Sm}\} \times \{\text{St,Te}\}$	No	No	VGG	No	LSTM	0.13	0.023	0.14	0.033
10	—	$\{\text{Sm}\} \times \{\text{St,Te}\}$	No	No	VGG	No	BiLSTM	0.19	0.009	0.21	0.006
11	—	$\{\text{Sm}\} \times \{\text{St,Te}\}$	No	No	Resnet	No	BiLSTM	0.21	0.008	0.23	0.007
12	—	—	Yes	No	—	No	BiLSTM	0.07	0.311	0.09	0.285
13	1D-CNN	$\{\text{Sm}\} \times \{\text{St,Te}\}$	No	No	VGG	No	BiLSTM	0.35	<0.001	0.39	<0.001
14	1D-CNN	$\{\text{Sm}\} \times \{\text{St,Te}\}$	Yes	No	VGG	No	BiLSTM	0.35	<0.001	0.40	<0.001
15	1D-CNN	$\{\text{Sm,A,Sa}\} \times \{\text{St,Te}\}$	Yes	No	VGG	No	BiLSTM	0.39	<0.001	0.46	<0.001
16	1D-CNN	$\{\text{Sm,A,Sa}\} \times \{\text{St,Te}\}$	Yes	Yes	VGG	No	BiLSTM	0.47	<0.001	0.53	<0.001
17	1D-CNN	$\{\text{Sm,A,Sa}\} \times \{\text{St,Te}\}$	Yes	Yes	VGG	Yes	BiLSTM	0.51	<0.001	0.58	<0.001
18	TCN	$\{\text{Sm,A,Sa}\} \times \{\text{St,Te}\}$	Yes	Yes	VGG	Yes	TCN	0.50	<0.001	0.56	<0.001
19	1D-CNN	$\{\text{Sm,A,Sa}\} \times \{\text{St,Te}\}$	Yes	No	Resnet	No	BiLSTM	0.40	<0.001	0.49	<0.001
20	1D-CNN	$\{\text{Sm,A,Sa}\} \times \{\text{St,Te}\}$	Yes	Yes	Resnet	No	BiLSTM	0.51	<0.001	0.56	<0.001
21	TCN	$\{\text{Sm,A,Sa}\} \times \{\text{St,Te}\}$	Yes	Yes	Resnet	Yes	TCN	0.55	<0.001	0.63	<0.001

TABLE 4: Prediction accuracy (Pearson correlation  $r$ , 2-tailed  $p$ -value) on the UVA Toddler dataset of 21 different models to estimate CLASS Positive Climate and Negative Climate. St=student, Te=teacher, Sa=Sadness, Sm=Smile, A=Anger, DT=Decision Tree.

Confusion Matrices: Machine-Human						
Positive Climate				Negative Climate		
1	2	3	4	5	6	7
1	0	0	0	0	0	0
2	0	0	0	.03	.03	0
3	0	.14	.41	.07	.08	.03
4	0	.43	.25	.53	.18	.13
5	0	0	.16	.14	.47	.14
6	0	.43	.14	.15	.16	.55
7	0	0	.04	.08	.08	.15

Confusion Matrices: Human-Human						
Positive Climate				Negative Climate		
1	2	3	4	5	6	7
1	0	0	0	0	0	0
2	0	.5	.06	.03	0	0
3	0	.17	.5	.03	.02	.04
4	0	.33	.13	.68	.18	.09
5	0	0	.06	.15	.6	.13
6	0	0	.25	.11	.2	.73
7	0	0	0	0	0	.01

TABLE 5: **Top:** Normalized confusion matrices of the machine (model #21) versus human CLASS coders on the UVA Toddler dataset. Rows are the (rounded) predictions; columns are ground truth. **Bottom:** Inter-coder (human) confusion matrices.

## 10.2 Results

Results are shown in Figure 4. The Pearson correlations of the predicted w.r.t. ground-truth CLASS scores increased almost monotonically as  $k$  increased from 2 to 10 (corresponding to a training set size of about 380 video segments up to 3874) for both PC and NC. At  $k = 10$ , accuracy for both PC and NC is still increasing, though the curve is flattening slightly for PC. This suggests that significantly more accuracy can be gained simply by adding more training data, even using this shallow architecture with purely auditory features. In terms of number of model complexity, the accuracy of the forest increased with  $n$

for almost all  $k$ . There were, however, diminishing returns above  $n = 35$  decision trees.

Based on these results, we trained a final random forest ( $n = 35$  since it was simpler and gave equivalent accuracy to  $n = 50$ ) on all 10 folds of training data and evaluated it on the 2000 test videos; this achieved Pearson correlations of 0.36 and 0.41 on PC and NC, respectively. It is likely that the MET models suffered due to the relatively shallow models that we trained, but that they also benefited from having much more training data compared to UVA Toddler.

## 10.3 Confusion Matrices

Similar to Section 9.2, we calculated the inter-coder reliability of human CLASS coders on MET. The inter-coder Pearson correlations on the MET dataset, as assessed on the 1044 video segments that were double coded, were 0.42 and 0.51 for PC and NC respectively. (Spearman correlations were slightly higher at 0.48 and 0.53.) These are higher than the machine's accuracy but not dramatically so. We also calculated both the machine-human and human-human confusion matrices for PC and NC on the MET dataset; see Table 6. For both cases, it does occasionally happen that one coder may assign a score that differs by 3 levels from another coder's assigned score. There is no obvious trend that the machine makes egregious errors much more often than human coders do.

## 11 IDENTIFYING KEY CLASSROOM MOMENTS

Arguably the most impactful opportunities of AI-enabled classroom observation are to give specific feedback about *particular moments* in a classroom session. Moving from aggregate analysis to the specific is a big research challenge: Machine learning-based systems to detect and track faces, recognize emotional states, and other perceptual tasks often perform with high accuracy on average but can nonetheless make embarrassing mistakes on specific

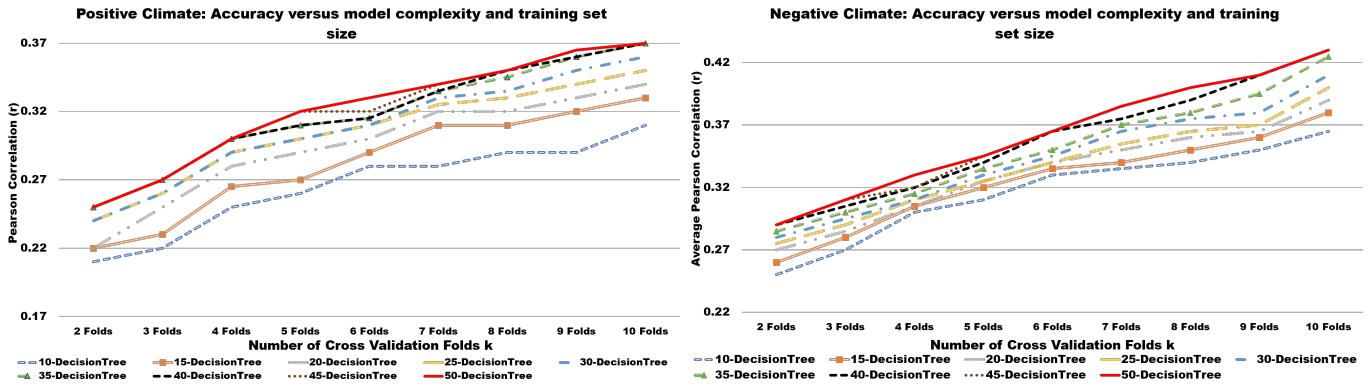


Fig. 4: Pearson correlation between predicted and human-coded CLASS scores on the MET dataset. Each model was trained as random forest of  $n$  trees on  $(k - 1)$  training folds and tested on the remaining fold. **Left:** Positive Climate. **Right:** Negative Climate.

Positive Climate								Negative Climate							
	1	2	3	4	5	6	7		1	2	3	4	5	6	7
1	.4	.4	.15	0	0	0	0	1	.8	.1	.1	0	0	0	0
2	.3	.4	.25	.1	.1	0	0	2	.1	.6	.2	.05	0	0	0
3	.3	.2	.5	.1	.1	0	0	3	.05	.2	.4	.05	0	0	0
4	0	0	.1	.5	.2	.1	0	4	.05	.04	.2	.7	0	0	0
5	0	0	0	.1	.4	.25	0	5	0	.03	.1	.1	.8	1	0
6	0	0	0	.1	.17	.6	.4	6	0	.03	0	.1	.1	0	0
7	0	0	0	.1	.03	.05	.6	7	0	0	0	0	.1	0	1

TABLE 6: **Top:** Normalized confusion matrices of the machine (model #21) versus human CLASS coders on the MET dataset. Rows are the (rounded) predictions; columns are ground truth. **Bottom:** Inter-coder (human) confusion matrices.

people or at specific moments. In this section we explore some approaches to finding automatically the most important classroom interactions within a 15-min video segment, similar to some prior work on video summarization [22], [67], [68]. In particular, we focus on distinguishing moments (45-90seconds long) that exhibit very *low* PC from moments that exhibit very *high* PC. (Since labeling at this short timescale is novel and outside the purview of the CLASS Manual, we decided not to label “intermediate” PC so as to make the task more tractable for human coders.) This is a binary classification problem, and we measure accuracy as the Area Under the ROC Curve (AUC), which equals the probability that the machine, when presented with a moment with high PC and a moment with low PC, can correctly distinguish which is which. If successful, such a tool could help teachers to identify the key moments containing either very high or very low PC, and to understand *when* and *why* their interactions with students were particularly effective. Our summarization problem is *supervised* because the moments we want to find depend on a particular CLASS dimension (PC). To tackle this problem, we collected more labels for the UVA Toddler dataset, and we explored four different algorithmic approaches.

### 11.1 Dataset

We recruited several coders from the University of Virginia’s Curry School of Education who were trained in the CLASS to watch the UVA Toddler videos and to find several clips within each video that exhibit “high” Positive Climate and several clips that exhibit “low” Positive Climate; the clips ranged from 45-90 sec. We also asked the coders to give a brief description explaining the reasoning behind their given label. For instance, for one moment rated as low PC, the coder noted “no interaction between kids and teachers – students are not interacting with each other either”. For a moment rated as high PC, the coder noted the presence of “enthusiastic and animated tones”. In total, 717 labeled clips were obtained. We split these labeled clips using the same cross-validation folds as our previous experiments on UVA Toddler.

### 11.2 Approach 1: Stepwise Output of TCN

The first approach we tried was to train a *momentary* binary classifier of “high/low PC” (one output per timestep) jointly with the *aggregate* detector that estimates one CLASS PC score for the whole 15-min video segment (one output at the end of the entire sequence), i.e., adding a secondary task to predict low/high PC moments. Our aim here was to determine if joint training to predict PC score for the whole video and low/high PC moments led to an improved model performance by learning generalized features. To this end, we expanded the TCN in model #21 to output a prediction at each timestep to indicate whether that moment was associated with “high” (1) or “low” (0) PC. We then added binary cross-entropy loss terms to all timesteps  $t$  that coincided with a clip for which a human-coded label (high or low PC) was provided. The model also included a 7-way cross-entropy loss for the aggregate PC score. As in all our experiments on the UVA Toddler dataset, we trained and tested the models in a 10-fold cross-validation fashion.

**Results:** The average (over all folds) AUC (Binary classification task) for determining whether each moment exhibited high/low PC was only 0.39 – worse than guessing. Also, the Pearson correlation of predicting CLASS PC itself (1-7) decreased considerably to 0.47 (down from 0.55). This suggests that aggregate CLASS score estimation might not decompose trivially into the average of many momentary predictions.

### 11.3 Approach 2: Binary Classification

Here we trained a TCN-based binary classifier that analyzes individual, variable-length video clips (45-90sec) and estimates

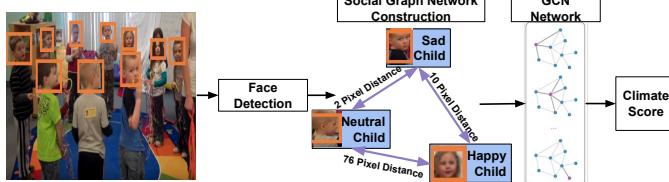


Fig. 5: Analyzing a classroom scene as a social network using a Graph Convolution Network.

via a logistic sigmoid unit whether the clip exhibits high or low PC. In contrast to Approach 1, this model does not also try to estimate aggregate PC. We compared two architectures: (1) model #21 but without the auditory pathway; (2) the full model #21 with the auditory pathway.

**Results:** The TCN with only visual information did not perform well: the average AUC was 0.35 (worse than chance). However, using the audio information, the AUC improved slightly to 0.58 and was statistically significant (Wilcoxon sign-rank test,  $p = 0.009$ ). Based on the information we collected from the human coders explaining *why* they rated each clip as high/low PC, we speculate that the auditory behavioral markers of Positive Climate – e.g., the degree of warmth and positivity in a teacher’s voice – might be easier to detect. In contrast, some of the visual features predictive of high/low PC involved more complex interactions such as “taking turns with the kids playing basketball and showing them how to shoot” (as was labeled by a coder for one video).

#### 11.4 Approach 3: GCNs for Social Network Analysis

Motivated by recent deep learning architectures for graphs [21], we explored whether there is underlying information that could be extracted from the classroom by viewing it as a social graph of interactions between students and teachers (see Figure 5). Graph convolution has become popular in recent years and impacted a variety of related fields in affective computing, e.g., group emotion recognition [69]. In our work, we trained a Graph Convolutional Network (GCN) [21] by constructing a graph from the detected classroom participants: Each detected face in each video frame is a node, and the weighted adjacency matrix of nodes in each frame is calculated as the inverse pixel distance (in 2-D space) between the centers of the face boxes. To lessen the effect of false alarm face detections, we capped the number of detections in each frame to 22, which is the maximum number of participants in any UVA Toddler classroom. To each node we associated a 4-dimensional feature vector consisting of the three probabilistic predictions of sadness, anger, and smile, as well as the child/adult probability according to the automatic face classifiers.

To classify a short video clip as high/low PC, we constructed a social graph for each video; applied two sequential graph convolution operations (100 filters each), each followed by a ReLU activation and dropout layer; and then computed a sum over all features in the graph weighted by attention scores, similar to Section 8.5. While attention-based pooling methods have been proposed before [70], our attention mechanism is applied on the output graph after graph convolution. The idea behind the attention is that we can identify the key participants present in each video frame using the self-attention weights. It also condenses the graph into a fixed-length representation. We found that both the attention mechanism and dropout were essential to obtain good performance

with the GCN. Finally, we aggregate the feature vector for all frames over time using a BiLSTM (3 layers deep, 10 hidden units). Our models were trained with Adam as the optimizer, using an initial learning rate of 0.001 for 100 epochs, using the same cross-validation folds as the other UVA Toddler experiments.

##### 11.4.1 Does topology matter?

Within a larger network, a GCN layer computes a non-linear aggregation of feature vectors from multiple nodes, weighted according to the graph Laplacian matrix induced by the graph topology. To explore whether the graph topology of *who is where when* was actually important, or whether the GCN simply averages over *all* participants’ *individual* features rather than examining *interactions* between them, we compared the GCN approach described above to the following two alternatives: (1) We set the normalized Laplacian matrix that encodes the graph topology to be the identity matrix  $I$ . In this case, each node in the graph is completely isolated, i.e., each node is only connected to itself. (2) We set the normalized Laplacian matrix to be a uniform matrix with all entries equal to the value  $1/d$ , where  $d$  is the number of nodes in the graph. In this case, the graph is a clique (with self-connections).

**Results:** Using the graph topology induced by the actual face detections, the average AUC across the 10-folds, for discriminating high from low PC, was 0.70 ( $p = 0.005$ , Wilcoxon sign rank test). Though it still allows room for improvement, this is the best result out of all the approaches we tried for detecting high vs. low PC in short video clips. In comparison, the AUCs obtained for either the identity or the uniform adjacency matrices were at-chance (0.48 and 0.52, respectively). This suggests that the topology of *who is where and interacting with whom when* is important for estimating classroom PC. Also, it is noteworthy that the GCN model which analyzes only the emotion and age data performs better than the approach in Section 11.3 based on model #21, which analyzes the entire image, audio features, along with the aggregate emotion data for individual frames over the entire sequence.

#### 11.5 Approach 4: Siamese Network

In contrast to Approaches 1, 2 & 3 above that try to classify a video clip as high vs. low PC on an absolute scale, here we explore a state-of-the-art video highlighting and summarization approach [22] that uses a Siamese network to takes two video clips from the *same* video and output which of them exhibits *higher* PC. The two inputs to the network (one from each clip) are produced by the TCN in model #21 that was modified to produce a scalar. Then, these two scalars are processed non-linearly by a 2-layer dense neural network (2 hidden neurons each) and a logistic sigmoid unit to indicate whether the first clip (0) or second clip (1) has higher PC. Since we were uncertain whether this Siamese architecture would work for key-moment prediction, we implemented a “positive control”, i.e., we trained a similar model to distinguish between two whole 15-min video segments – one with high ( $\geq 4$ ) and one with low ( $< 4$ ) PC.

**Results:** Despite a hyperparameter search over the TCN dilation stride, number of residual blocks, learning rate, etc., we were not able to train the key-moment prediction network using the Siamese architecture – the training loss never decreased significantly. Interestingly, the positive control, despite needing to analyze a much longer time series (15min vs. 45-90sec) was able

to solve its task effectively and achieved an average AUC of 0.82 (averaged over all 10 cross-validation folds). This suggests that identifying key moments with high/low PC may be a harder task than estimating the aggregate PC score over an entire video, or it might require a very different architecture and set of features than the aggregate PC estimation problem.

## 12 CONCLUSIONS

We devised a multi-modal machine learning architecture and training procedure to create an Automatic Classroom Observation Recognition Network (ACORN). The ACORN is, to our best knowledge, the first fully automated system that can analyze videos of school classrooms and estimate the Positive Climate (PC) and Negative Climate (NC) dimensions of the CLASS protocol. The best system (model #21) presented in this paper can predict PC and NC with an accuracy (Pearson correlation) of 0.55 and 0.63 w.r.t. labels provided by expert CLASS coders, which is a substantial improvement on our earlier work [15] (with Pearson correlations of 0.40 and 0.51 w.r.t. ground-truth). These accuracy levels are similar to inter-coder reliability of human coders. We also presented statistically significant results (AUC=0.70) on automatically detecting the key moments within a classroom video when PC is higher or lower.

### 12.1 Main Results

Below we summarize the main empirical results of our paper: **Temporal integration:** (1) Temporal integration using a Temporal Convolutional Network delivers similar accuracy but is substantially faster than a BiLSTM for both training and testing. (2) The inclusion of additional upstream modules (Here upstream modules are neural networks that extract features from the different information pathways) and information pathways (facial expressions, separate emotion estimates of teachers and students, whole image frame, etc.) are more critical than the choice of the downstream temporal modules (Here downstream modules are temporal networks that integrates the various inputs from the upstream modules such as BiLSTM, TCN, etc.). (3) Students' and teachers' emotional dynamics, not just their average emotion values, are important for estimating PC and NC.

**Choice and quality of features:** (4) Improved accuracy in upstream modules (e.g., switching from VGG-16 to Resnet-50 for face and image analysis) translates into improved accuracy in downstream model predictions (CLASS scores). In other words, accuracy improvements in early perceptual layers can persist throughout the entire computational graph. (5) While human-interpretable features such as facial expressions are useful for predicting CLASS scores, substantial complementary information can be gleaned, albeit at the price of interpretability, from analyzing low-level inputs such as spectral audio features and the pixels of each whole video frame.

**Auditory pathway:** (6) Auditory features already provide non-trivial predictive power (reaching correlations around 0.30), but adding visual features provides complementary information that raises the accuracy even higher (to around 0.60). This is important to consider when weighing privacy versus accuracy. (7) When using only the auditory pathway, similar accuracy was achieved for both the UVA Toddler and MET datasets, despite different age groups and different CLASS protocol definitions. (Note that no conclusion is available for the visual pathway since we could not test it on the MET dataset.)

**Training set size:** (8) CLASS PC and NC prediction accuracy of the auditory pathway increases steadily up to 3500 training examples (15-min video segments); the trajectory suggests it will continue to increase.

**PC vs NC:** (9) We consistently obtained higher accuracy in predicting NC compared to predicting PC for both the UVA and MET datasets.

**Predicting key moments:** (10) Predicting the key moments when the Positive Climate is high/low seems to be a harder task than estimating the aggregate CLASS score. This is possibly because many momentary perceptual errors can "average out" over many timesteps. Across several different approaches, including a CNN+TCN, Siamese network, and GCN+BiLSTM, we found that the graph convolution-based approach worked best because it can harness interactions between different participants weighted by their proximity to each other. To our knowledge, this is one of the earliest results in the literature on applying deep graph convolution to classify social interaction between humans.

### 12.2 Future Research

There are several directions and research questions we are considering and/or actively exploring. To improve model accuracy, we are exploring: (1) How do we include more powerful linguistic information for CLASS score prediction that goes beyond what the low-level spectral audio features can capture? One possible approach is to train a classifier that can estimate the language complexity of an audio clip as an additional feature. (2) It may be useful to track the expression trajectories of individual people in the classroom over time, rather than just treating each frame as a "bag" of expressions. (3) There is ample room to explore harnessing the GCN approach that we used for key-moment prediction for overall CLASS score estimation. (4) Does the architecture for PC and NC generalize to other CLASS dimensions? Which additional features would be needed?

Ultimately, the most important research question is about how to make automated classroom observation more useful for teachers: (5) Is the accuracy of our current ACORN (model #21) high enough to provide useful teacher training and professional development experiences? We are in the early stages of conducting an experiment to see how teachers can use the outputs of our system to become more perceptive of classroom interactions and eventually to implement more effective interactions in their own classrooms.

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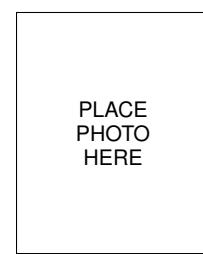
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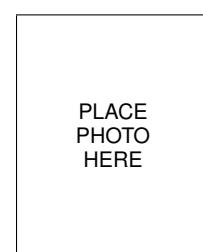
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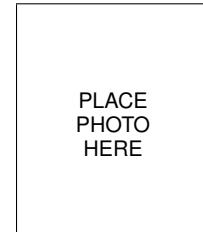
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