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The Future Belongs to the Curious: Towards Automatic Understanding and Recognition of Curiosity in Children

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Abstract

Curiosity plays a crucial role in learning and education of children. Given its complex nature, it is extremely challenging to automatically understand and recognize it. In this paper, we discuss the contexts under which curiosity can be elicited and provide an associated taxonomy. We present an initial empirical study of curiosity that includes the analysis of co-occurring emotions and the valence associated with it, together with gender-specific analysis. We also discuss the visual, acoustic and verbal behavior indicators of curiosity. Our discussions and analysis uncover some of the underlying complexities of curiosity and its temporal evolution, which is a step towards its automatic understanding and recognition. Finally, considering the central role of curiosity in education, we present two education-centered application areas that could greatly benefit from its automatic recognition.

Index Terms: Curiosity, Emotion recognition, child-computer interaction

1. Introduction

Curiosity may have killed the cat, but it is one of the critical factors in learning and education of children. Previous research has shown that curiosity is as important as intelligence and it is one of the most important factors in academic performance of students [1]. Teachers can inspire curiosity in students to keep them engaged and to facilitate their learning process [1].

When a person is curious about something, the activity in the hippocampus, the area of the brain that is involved in creating memories, increases [2]. There is also an increase in the activity of the brain circuit that is related to reward and pleasure which rely on dopamine. Curiosity prepares the brain for better learning and remembering completely unrelated information [2]. If a teacher is able to arouse curiosity in students, they are better prepared to learn things that they might otherwise consider difficult or even boring and this stimulation can make further learning more enjoyable. Curiosity is also connected to analytic ability, problem solving skills and intelligence, which suggest that greater curiosity can make you smarter [3, 4].

Although there has been a considerable amount of research on automatic recognition of learning-centered affective states such as engagement, frustration and boredom [5, 6], curiosity has remained fairly unexplored. We are aware of only two studies related to automatic recognition of it [7, 8]. One of the possible reasons for this, is the complex nature of curiosity. In order to design computational models for recognizing curiosity, one must understand different kinds of curiosity, the context under which it can be elicited, behaviors that are related to it and the individual differences in expressing it.

In this paper we discuss different contexts under which curiosity can be elicited as well as provide a taxonomy of curiosity and the personality traits that can affect the expression of it. We provide some evidence of co-occurring emotions with curiosity and analyze the valence, positivity and negativity, of curiosity in a gender-specific manner. We then study the behavior indicators that are related to curiosity and provide possible ways of automatically recognizing them. Finally, we discuss two major application areas that will greatly benefit from automatic recognition of curiosity.

2. Elicitation of curiosity

Curiosity is a complex affective state, which is the product of several functions of the mind [9], and it can be elicited in different ways and under different contexts. According to Tieben et al. [10] curiosity can be elicited using five main principles: 1) Novelty - when the person is experiencing a new situation or getting to know a new problem/object; 2) Partial exposure - when the person is exposed only to a part of information, which is incomplete, or when there is a gap between the knowledge of a person and what is being observed or experienced; 3) Complexity of a situation/object - where the situation/ object has ambiguity and further effort is needed for clarification; 4) Uncertainty - when the person is doubtful about something or is surprised by finding out the truth about something; 5) Conflict - where the expectations of a person are violated and the person has conflicting experiences and ideas. Loewenstein [11] states that the situations that are perplexing or that are new or surprising, lead a person to an awareness of a gap in their knowledge or understanding. Such a gap causes feelings of deprivation and arouses the desire to obtain the knowledge to reduce or eliminate this feeling. With this definition one has to have some prior knowledge of the subject to have any kind of gap. As discussed, depending on the context that curiosity has been elicited, the expressions of curiosity might differ. Thus, it is important to consider the role of context, when seeking to automate understanding and recognition of curiosity.

Curiosity has also been defined as a need, thirst or desire for knowledge about something [12], which can mean the curious person is uncertain about some aspects about the topic. Discovering knowledge about that topic can be surprising especially if it is contradictory to one's previous beliefs. If the desire to obtain knowledge on the subject is very strong the person might experience excitement towards the subject. Depending on the stimulus that is eliciting curiosity, one can express anxiety or fear, which might be caused by uncertainty, lack of knowledge and anticipation of unpleasant outcomes, frustration, anger, embarrassment or even sadness, due to the challenges faced in

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Figure 1: *Illustration of the five types of tasks performed by children in EmoReact dataset. The experimenters are behind the scenes and the children talk to them while their reactions are being recorded.*

knowledge discovery or the outcomes of their exploration. The outcome of knowledge discovery can cause happiness in one because of the sense of relief and achievement that it causes.

3. Taxonomy of Curiosity

Researchers have differentiated between different kinds of curiosity. Two major distinctions between types of curiosity are as follows: (1) State curiosity vs. trait curiosity: state curiosity is evoked as a reaction to an external situation, while trait curiosity is related to someone's internal characteristics and interest towards learning [13]. (2) Sensory curiosity vs. perceptual curiosity: sensory curiosity is caused by an external stimulus with novel, complex, uncertain, or conflicting properties, while perceptual curiosity involves interest in and giving attention to novel perceptual stimulation, and motivates visual and sensory-inspection [14].

Previous research has investigated the role of personality in expressing curiosity [15, 16, 17, 18]. Based on their findings personality traits of children such as openness, sensation-seeking, inhibitory control, hyperactivity-inattention, anxiety, anger, depression and shyness correlate with curiosity and can affect how a child experiences and shows curiosity. For example, if a child is depressed, they probably will experience and show state curiosity rather than trait curiosity.

It is also important to consider the role of time in discovering the desired knowledge and co-occurring emotions with curiosity. Marret et al. [19] have investigated the effect of time on curiosity. Their findings suggest that the time spent by individuals for filling the knowledge gap and transitioning from not knowing to almost knowing and their personal approximation of this time can affect their experience of curiosity and the intensity of positive affect, annoyance and discomfort they are experiencing.

4. Empirical Analysis of Curiosity

For our analysis of curiosity, we have used the EmoReact dataset [8], which has 385 video samples of curiosity expressed by children under different contexts. In this section, we provide an empirical analysis of co-occurring emotions with curiosity and the valence of curiosity in a gender-specific way. We also show some qualitative results of expressing curiosity by different individuals and under various contexts.

4.1. Dataset

EmoReact is a newly collected dataset of children aged four to fourteen years old. In total it contains 1102 clips that are labeled for 17 affective states including curiosity. In these video clips, children react to 37 different subjects that include food, technology, YouTube videos and gaming devices.

In these videos, children face a series of events with an anticipated but unknown resolution. The subjects that children are reacting to are unknown to them before the recordings, which can evoke curiosity. Children perform the following tasks in the videos: (1) getting to know the subject by its being shown: these subjects have been selected in a way that they are not obvious to the children and there is an element of expectancy and surprise in them; (2) being asked a question about the subject: when children encounter questions they are more likely to get curious and seek answers especially if it is a novel or complex subject; (3) answering a question about the subject; (4) being told a fact about the subject and reacting to it: showing children that you have information about something can make them more curious as no one likes to be the last person to know a certain fact; and (5) explaining ones opinion about the subject. Figure 1 shows a visual illustration of these tasks. Each video clip contains only one child who is reacting to one specific subject. In total there are 63 children of which 31 are male and 32 are female and the annotations for identities and genders are provided. These annotations enable person-independent, gender-specific and person-specific analysis.

The choice of emotion labels in this dataset was done with an emphasis on affective states that are important for learning and education based on previous research [5, 20]. The full list of the labels includes six basic emotions (anger, disgust, fear, happiness, sadness and surprise), neutral, curiosity, uncertainty, excitement, attentiveness, exploration, confusion, anxiety, embarrassment, frustration and valence.

Each short clip has been annotated by three independent crowd workers who were recruited from the online crowd sourcing platform, Amazons Mechanical Turk (MTurk) to obtain the labels [21]. The definitions of each label was included in the annotation interface for consistency. The definitions provided for emotion labels in the annotation interface are as follows: Angry: Having a strong feeling of or showing annoyance, displeasure, or hostility; Happy: Feeling or showing pleasure or contentment; Surprised: Feeling or showing surprise; Disgusted: Feeling or showing strong dislike for something that has a very unpleasant appearance, taste, smell, etc.; Sad: Feeling or expressing grief or unhappiness; Fearful: Being scared of and appearing ready to escape something bad or unpleasant; Frustrated: Feeling annoyance caused by being unable to do something; Curious: The desire to learn or know more about something or someone; Uncertain: Feeling of being doubtful or unsure about something; Excited: Being eager and enthusiastic and interested; Attentive: Wishing focused and exhibiting concentration on someone or something; Explorative: Investigating, examining, and inspecting an object or topic; Confused: Being unable to understand or being perplexed because of con-

Figure 2: *Example frames of videos in EmoReact showing the co-occurrence of fourteen states with curiosity. Note that people in all of these videos have been labeled as curious while they were expressing one or more emotions during the same video clip.*

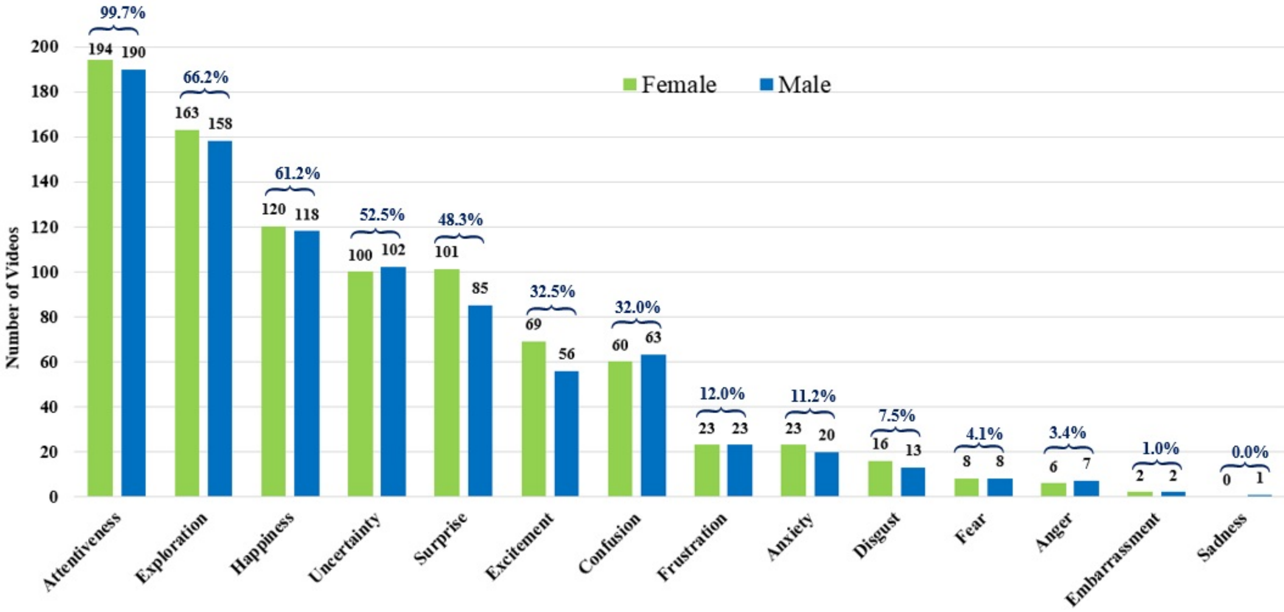

Figure 3: *Co-.occurrence of curiosity with different affective states in 385 videos labeled as curiosity. This Figure shows the number of videos in which curiosity has co-occurred with each affective state which are expressed by females and males and the overall co-occurrence percentage of each emotion label with curiosity . Note that attentiveness, exploration, happiness and uncertainty are the top four co-occurring states that are co-occurring with curiosity.*

tradiction between immediate experience and previous knowledge or belief; Anxious: Feeling uneasy, nervous, or apprehensive about something with an uncertain outcome; Embarrassed: Feeling or showing embarrassment or shame.

After collection of labels from MTurk, Kripendorffs alpha [22] has been used to evaluate the agreement level between workers. The agreement levels for different labels are as follows: Happiness: 0.57; Surprise: 0.63; Disgust: 0.61; Fear: 0.43; Curiosity: 0.41; Uncertainty: 0.47; Excitement: 0.43; Frustration: 0.54, Exploration: 0.24; Confusion: 0.29; Anxiety: 0.31; Attentiveness: -0.16; Anger: 0.28; Sadness: 0.23; Embarrassment: 0.09; Valence: 0.65; Neutral: 0.37. Agreement level between 0.4 and 0.6 shows moderate agreement and values between 0.6 and 0.8 show substantial agreement level between raters [23]. These agreement levels compare favorably to previous work in affective computing [24]. The annotations are provided on a Likert scale from 1-4 for all emotion labels except valence, which is annotated on a scale from 1-7; representing strongly negative to strongly positive. Each emotion has been expressed by a large number of children and, among the 1102 video clips, 385 videos have been annotated as curious. We are focusing on these latter videos for the purpose of this paper.

4.2. Analysis

In order to analyze curiosity in more detail, we studied the frequency of co-occurrence of curiosity with fourteen affective states provided by EmoReact (see Figure 3). The co-occurrence has been calculated considering the presence of other affective

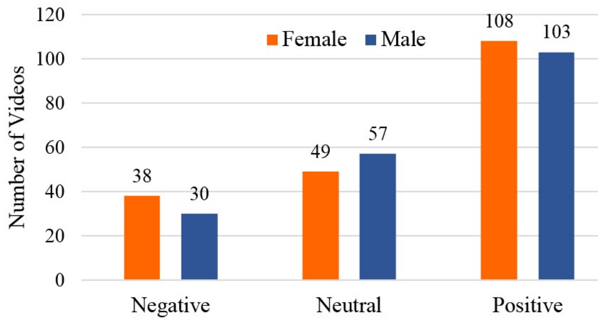

Figure 4: *Valence states of curiosity. This figure shows the bias towards positive valence in curiosity. Note that this analysis was done on 385 videos which were labeled as curious.*

states with curiosity in each video clip. As observed here, a person can be curious while experiencing other emotions at the same time. In order to be recognized as a curious person, one has to show focus and exhibit concentration on someone or something [10]. After being attentive to the subject, the curious person usually tries to study, examine or investigate a topic, an object or an event. This behavior has been labeled as exploration in EmoReact. As shown in Figure 3, attentiveness and exploration are the top two co-occurring emotions with curiosity. It is interesting to note that the frequency of expression of different affective states are equally distributed among females and males, while the way they express the emotions might differ [25].

As previous research has shown individuals can express emotions differently [26], we investigated individual differences in expressing curiosity. Figure 2 shows some of the qualitative results of such expressions. Although context has an impact on expression of curiosity, even under similar contexts individuals express curiosity differently. These differences can be because of age, personality traits and social background [15, 16, 17, 26].

Since curiosity is considered to activate the part of the brain that is related to reward and pleasure [2], we analyzed the negative, neutral or positive valence that co-occurred with curiosity to find out if there is a bias towards positive or negative valence. Figure 4 shows the results of this analysis. As shown in the Figure, there is a bias towards positive valence in curious expressions. We did not notice any gender differences in frequency of expressing positive, neutral or negative valence.

As discussed in this section, recognizing curiosity depends on many variables and there is no limited set of behaviors that can be used for this task, which makes it extremely challenging. In the following section, we will provide some of the visual, acoustic and verbal behavior indicators that could be helpful for automatic recognition of curiosity.

5. Behavior Indicators of Curiosity

The aforementioned discussions, show that there are different types of curiosity and, depending on the context and the individual, the behavior indicators of a curious person might differ. The following section summarizes some of the findings of previous research about the behaviors that are indicators of curiosity. These indicators include both verbal and nonverbal behaviors. Verbal behaviors are related to language and the words a person speaks while nonverbal behaviors include facial expressions, body posture, gestures, gaze behavior, speech quality and tone of voice. We provide approaches for measuring some of these behaviors automatically.

Here are some of the visual, auditory and verbal behaviors that are important for recognizing curiosity: (1) **Observing a new object**: depending on the type of the topic and the novelty of the topic to the individual, children spend some time just observing the new object and getting to know it. Attention towards the subject is one of the most important cues to recognize curiosity. Individuals tend to focus more on the subjects that are novel or unfamiliar over the more familiar ones, to make sense of them [27]. (2) **Inspecting the object**: children use their gaze to closely inspect an object and the observed behaviors from this stage are the vertical and horizontal gaze shifts, rotating the object and focusing on sub-parts of the object, moving around the object and changing the head orientation and position to fully inspect it. (3) **Carrying out manipulatory behaviors**: The behavior in which a child shows customary actions such as playing with the object, trying to find out how it operates, and determining its structure by loosening or detaching parts. (4) **Thinking**: When children get curious about a topic, it usually leads them to think about it; especially if they are uncertain, surprised or have conflicting ideas. (5) **Asking questions and making comments on the topic**: the number of questions the child asks or the comments s/he makes on the topic correlates positively with curiosity [17, 15]. Some children verbally express their interest or preference more than the others. (6) **Dominating the interaction**: children who are curious might dominate the interaction more than the non-curious children. This observation is consistent with the findings of Kashdan et al. [28] who showed that domination correlates positively with curiosity.

Although these behaviors are complex, some of them can be measured automatically using current technology while others are more challenging to measure. For instance, there has been a considerable amount of work on automatic recognition of action units and gaze behavior [29]; however, body gesture recognition is still in its initial steps. Also, speech recognition for children is still a challenging problem [30]. There has been very little research on automatically measuring curiosity [7, 8]. The results of such findings highlight the role of gaze behavior (vertical and horizontal gaze shift), number of blinks, head rotation, breathiness or tenseness of speech and energy of speech in recognizing curiosity.

Furthermore, it is worth mentioning that, although the target task is understanding and recognizing curiosity, the cues that are used to recognize the emotions that frequently co-occur with curiosity provide valuable information towards the desired task. Behavior indicators that can be automatically extracted and have been used in emotion recognition research can be categorized into three major categories:

Visual indicators: head orientation and movement, gaze shifts, head nods, head shakes, activation of action units such as brow raiser, jaw drop and blink are some of the most popular behavior indicators used in emotion recognition [8, 31, 32, 33] that can be extracted using publicly available tools such as OpenFace [34].

Acoustic indicators: voice quality features such as normalized amplitude quotient (NAQ), parabolic spectral parameter (PSP) and maxima dispersion quotient (MDQ) which are used to measure the tenseness, creakiness or breathiness, prosody features such as pitch of the voice which shows the energy level of speech signal are among the top used features for emotion recognition though auditory channel [29]. COVAREP is one of the publicly available tools that can be used to extract these features [35].

Verbal and para-verbal indicators: The words someone speaks such as beginning a sentence with "how", "why" or "what" can be indicators of some behaviors such as asking questions. Para-verbal indicators such as pause-fillers (um, uh), articulation rate and mean span of silence can also provide information about the uncertainty, excitement or exploration state of the child.

Multimodal analysis: Considering the complex nature of curiosity, a multimodal approach for recognizing it might be more appropriate, as it takes advantage of all information that can be obtained from a person. As an example, consider a child who is presented with a new object. Lets assume that expressing curiosity starts with just observing the object, which can only be captured through the visual channel, since the child is not speaking. Then, the child expresses their curiosity by asking questions, which can be measured using verbal indicators. If the child is uncertain, excited or surprised by the object, these emotions can be captured through the auditory and visual channel, as well as spoken words that specifically indicates those states such as "not sure","wow", "I like".

Note that the analysis of these behavior indicators and initial multimodal model of curiosity has been done in a separate study, showing the effectiveness of some of these cues. However, as it is outside the scope of this paper we refer the readers to the original paper [8].

We believe that the complex nature of curiosity requires building complex models that take into account the comprehensive factors that are involved in expressing curiosity. Recognizing the behavior indicators of curiosity and the co-occurring emotions using visual, auditory and verbal channels which also take into account the underlying temporal dynamics in evolution of affective states, is the first step towards automatic recognition of curiosity. The role of context, such as the way curiosity has been elicited, and personality of individuals should not be neglected either. This information can be obtained by questionnaires from individuals and experimenters, and the results could be used as input to the models. They can also be detected automatically using the aforementioned visual, acoustic, verbal and para-verbal indicators.

6. Application Areas

Children use computers for various purposes such as education and entertainment. It is important to better understand children, their needs and their relationships with technology to build well-designed systems that encourage children to interact. As educational use is one of the major purposes for which children use computers [36], it is important to design the optimal learning environment for them. As curiosity has a central role in learning and education, many systems can benefit from having an automated module for recognizing curiosity. In this section we describe two education-centered systems that can greatly benefit from having such a facility.

6.1. Adaptive Affect-sensitive Intelligent Tutoring Systems

An intelligent tutoring system (ITS) is a computer system that provides immediate and customized help or feedback to learners [37]. In traditional intelligent tutoring systems, the decisions for choosing the next steps for learning are mostly based on the performance of the students. For example, if their performance was evaluated as low or an answer provided to a question was wrong, they would have to review the content and retake the test before proceeding to the next step. However, the reason for poor performance is not always caused by not learning the material. Disengagement, boredom or anxiety and many other affective states can contribute to poor performance. Furthermore, traditional tutoring systems would often let the students decide when and how to use the facilities of the system and when to look for hints or helps. However, students tend to wait a long time before asking for help [38]. Therefore, it is important for a learning system to be aware of affective and emotional states of its users. In order to design tutoring systems that can effectively recognize affect, it is important to consider age, gender and individual differences in expression of emotions. Understanding and recognition of affect might be especially important as children are more impatient and need immediate feedback [39, 40]. To achieve this goal, a system should have the ability to perceive, understand, reason and infer the needs of each individual.

One of the ways to make this happen is by building personalized affect-sensitive tutoring systems. These systems could be individualized with regards to several considerations such as age, gender, personality traits, affective states, context and educational background and performance. These systems could provide flexibility and by choosing the right learning steps for each individual they could maintain a positive mental state for learners. As curiosity is one of the pillars of education, automatically recognizing and integrating it into ITS can have a big impact in learning and education. However, there has been very little done on building automatic curiosity detection systems; our work brings us closer to the goal by providing an analysis of behaviors related to curiosity.

6.2. Peer tutoring

Learning through peer tutoring has been shown to increase students' academic gains, including in student populations with intellectual and learning disabilities [41, 42, 43]. Further research has suggested that the tutors may gain more from the experience than the tutees [44, 45]. In recent years, several researchers have created software that replaces the tutee with a virtual agent and have found positive learning gains for students [46, 47, 48]; however, the majority of these studies have not included students with learning disabilities nor have these studies explored in depth the processes of knowledge communication from student tutors to their virtual tutees. Thus, leveraging virtual technologies that make delivering these experiences more individualized and effective, and building upon existing research to include students with learning disabilities, we are proposing to integrate the curiosity-focused emotion recognition described here into a virtual environment, TeachLivE [49], where the student participant speaks naturally to a peer avatar and the avatar, which is controlled by a human "interactor", responds verbally and non verbally to what the student participant says and does.

Analysis of the student's behaviors, including eye gaze, facial expressions and vocalizations can be automated, with more subtle aspects such as actual utterances being annotated by the interactor or a remote observer. One of our goals is to employ results of how and when children show curiosity to improve the communication of concepts between students and teachers. In essence, we believe that this research will provide insight into the communication of concepts by students, which in turn will suggest methods to improve instruction by their teachers.

7. Conclusions

Curiosity enhances learning and it is one of the fundamental factors in education. In this paper, we provided a taxonomy of curiosity and the contexts under which it can be elicited. We presented an empirical analysis of co-occurring emotions and the valence associated with curiosity in a gender-specific manner and provided some of the visual, acoustic and verbal behavior indicators of it. We found that there is a bias towards positive valence in expressions of curiosity and that attentiveness, exploration and happiness are the most frequently co-occurring affective states with curiosity. The analysis did not indicate any gender differences in frequency of expression of curiosity or any other emotions. Our study reveals some of the complexities of curiosity and provides guidelines and future directions towards automatic understanding and recognition of curiosity. Due to the central role of curiosity in education and learning, we pointed out two of the education-centered application areas that can significantly benefit from having an integrated capability to automatically recognize curiosity.

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