Predicting Affect from Gaze Data during Interaction with an **Intelligent Tutoring System**

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- O Introduction & Contributions
- Related Work
- MetaTutor
- O User Study & Eye Tracking Data
- Machine Learning Experiments
- Results
- O Conclusion & Future Work



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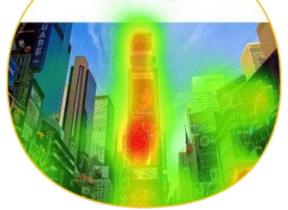
Introduction & Contributions

Gaze Replays



In what order did an individual look at things and for how long?

Heatmaps



Where did a **population** focus their visual attention?

Areas of Interest



How did a **population** focus on one element versus another?

Introduction & Contributions

- Using eye tracking data as a stand alone tool
- In contrast with hand-engineered heuristics for gaze-based interventions and other non-gaze features (e.g. pupil dilation)
- Investigate boredom and curiosity
- Identify features most predictive of each emotion



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Related Work

Emotions in Academic Setting

- Student motivation
- Academic achievement
- Boredom
- Engagement
- Emphatic & supportive tutor

Detect Learner's Emotions

- Interaction logs
- Acoustic and dialog features
- Physiological sensors
- Posture
- Questionnaires
- Eye gaze



"Unfortunately, positive emotions (including curiosity)

declined over the course of the interaction,

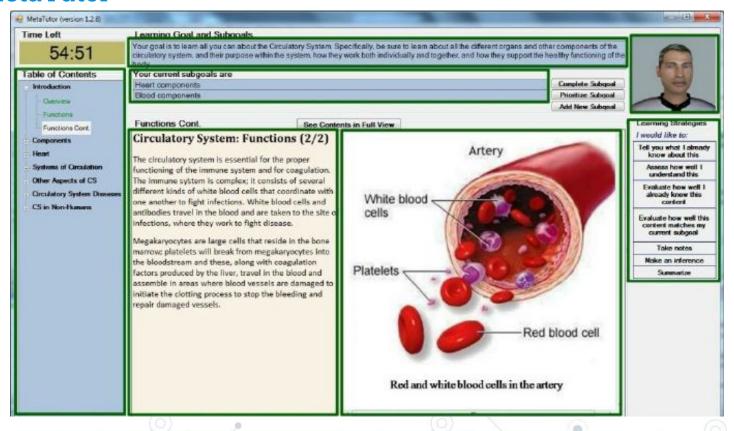
demonstrating a need for affective

interventions"

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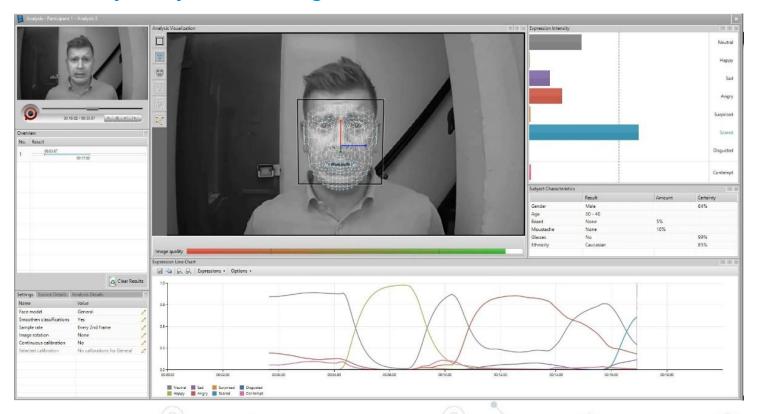
MetaTutor



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- 67 undergraduate students
 - 51 considered after data validation
- Used MetaTutor for about 90 minutes
- Data from number of sensors, including an eye tracker
- Self-reports
 - 5 per student
 - Likert scale between 1 (strongly disagree) and 5 (strongly agree)
 - Boredom: mean = 2.60, SD = 0.69
 - \circ Curiosity: mean = 2.93, SD = 0.71



Fixations: persistent focus on a single point

Saccades: paths between two consecutive fixations

166 features in total



Application-Independent

- Number of fixations
- Fixation duration
- Saccade length
- Angle between consecutive saccades
- Angle between a saccade and the horizontal plane

Application-Dependent:

- Duration of longest fixation
- Proportion of fixations and time spent
- Gaze transitions
- Time of first/last fixation
- Total fixation time

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Machine Learning Experiments

- Two separate binary classification problems: boredom and curiosity
- Emotion Present (EP) vs. Emotion Absent (EA)
- 10-fold cross validation
- Four algorithms used
 - Random Forests
 - Naive Bayes
 - Logistic Regression
 - Support Vector Machines

Machine Learning Experiments

- **Accuracy**: percentage of correctly classified data points
- **Cohen's kappa:** measure of classification performance which accounts for correct predictions occuring by chance
 - o 0 if the predictions were no more accurate than chance
 - o 1 when labels exactly match the ground truth values
- Feature reduction against overfitting
 - Principal Component Analysis (PCA)
 - Wrapper Feature Selection (WFS)

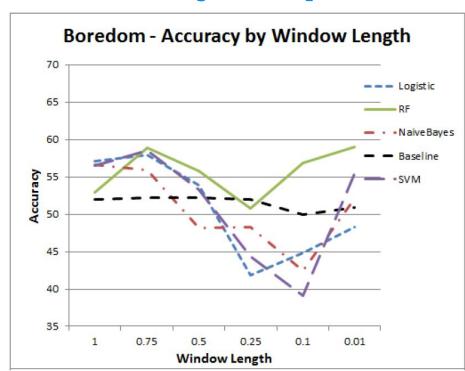
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- Related Work
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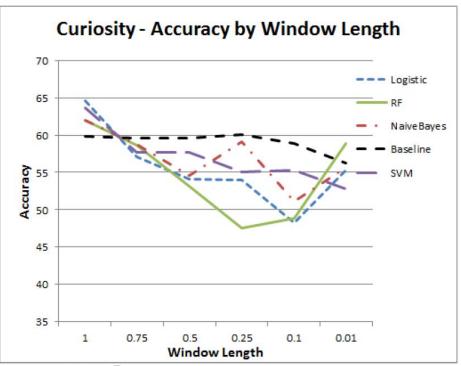


Predicting Self-Reports across the Interaction

- **Goal:** determine the amount of gaze data preceding the self-report that should be used for optimal prediction performance
- Baseline: a majority-class baseline, using t-tests with a Bonferroni adjustment
- Four 4x6 General Linear Models: boredom accuracy/kappa, curiosity accuracy/kappa as the dependent variables
 - 4 classifiers
 - 6 window lengths
 - Treat one train/test split as a single point

Predicting Self-Reports across the Interaction





Predicting Self-Reports across the Interaction

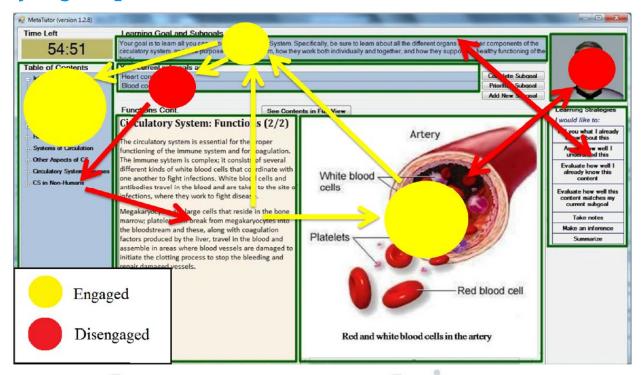
- No significant effects of the classifier
- Main effect of window length both for boredom and curiosity
 - Low p-value
 - High eta squared value
- Significantly better than baseline
 - Boredom at 75% and 100% (10.5 minutes and 14 minutes)
 - Curiosity at 100% (14 minutes)

"This study provides empirical evidence that [using a 20 second interval for affect labeling] may not always be appropriate, depending on the data used for prediction."

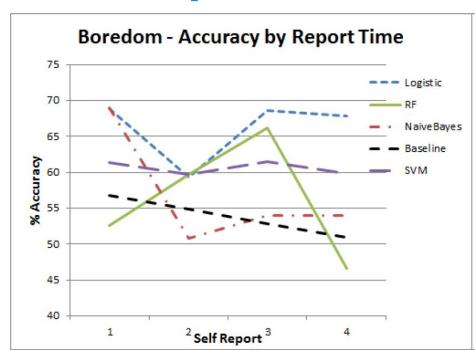
Identifying Important Features

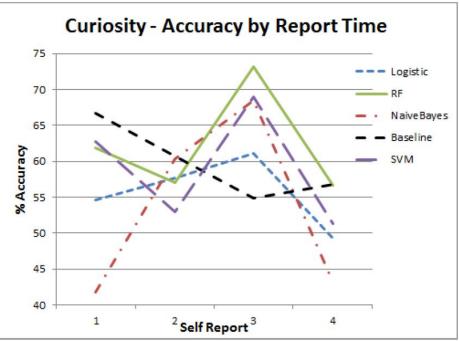
- Goal: examine features selected by the WFS process
- *Arrows:* gaze transitions
- *Circles:* features related to the AOI (circle size increases with the number of related features found)

Identifying Important Features



- Goal: improve performance by treating each self-report time as its own classification problem
- Four 4x4 General Linear Models
 - 4 classifiers
 - 4 report times



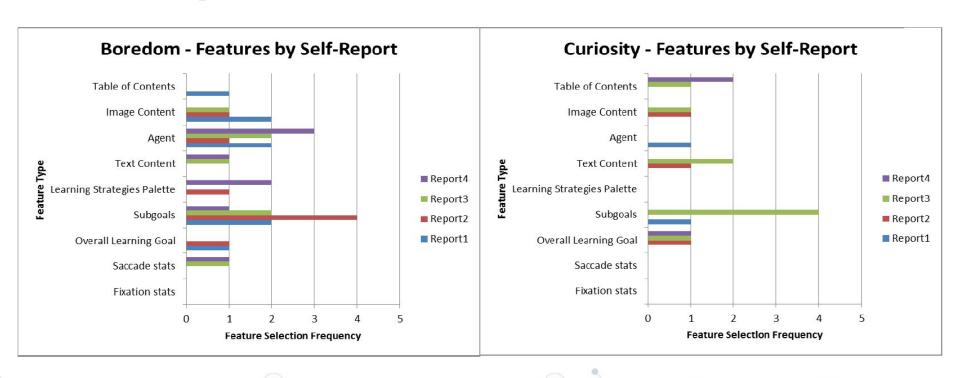


- No significant effects for boredom
 - Logistic Regression performing the best
 - Single self-report time results are better
- Effect of report time for both kappa and accuracy for **curiosity**
 - Amount of time spent interacting with MetaTutor affects the relationship between gaze and affect



"The results of this section seem to indicate the

"The results of this section seem to indicate that the relationship between gaze and affect varies over time. Different gaze features would be more informative at different report times."



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Conclusion & Future Work

Conclusion

- Eye gaze data alone a useful tool
- Longer intervals for predicting affect
- Temporal information can increase accuracy

Future Work

- Use additional data sources
- Develop intervention strategies

