Learning about Cognitive Disequilibrium and Flow:

An Exploratory Study

Mononito Goswami, Lujie Chen, and Artur Dubrawski

Motivation

Teaching how to solve real word problems is a fundamental goal of education

Math puzzles are an inexpensive way to teach young children problem solving

Studies have show that:

- Problem solving = Tension + Confusion + Joy (Emotional Roller Coaster)
- Young students need adult assistance due to their less accurate academic self-assessment

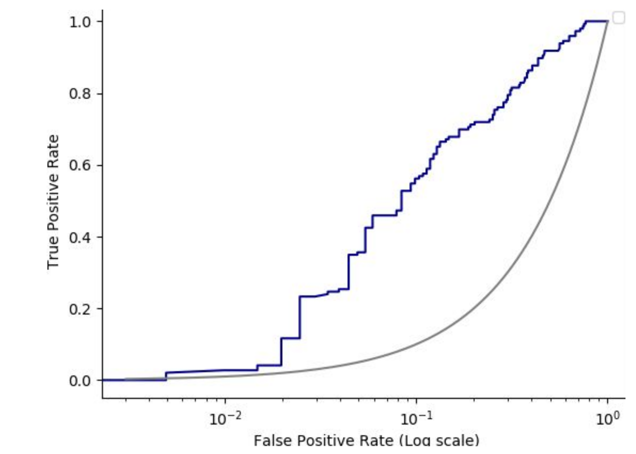
Coaching math problem solving is hard because:

- Student's cognitive states (Disequilibrium, Flow) are latent
- Teachers need to make *adaptive personalized* pedagogical decisions

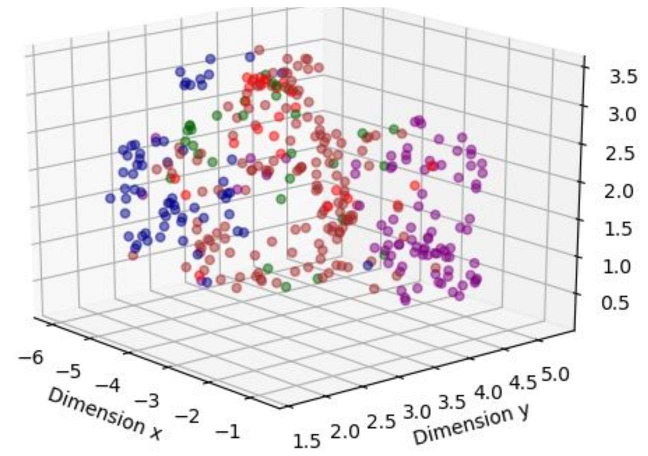
Coaching an entire class of students is harder because teachers have to make the same pedagogical decisions, but for a large and diverse set of students.

Solution: A decision support system that monitors the cognitive state of multiple students in real time and lessen the cognitive load on a teacher

Results



Pooled ROC curve: Flow state **AUC:0.831**



3-D UMAP embeddings

p-values from Kolmogorov-Smirnov test

	Gaze Velocity		Gaze Acceleration		Head Velocity		Head Acceleration	
	X	Y	X	Y	Translational	Rotational	Translational	Rotational
Approximate Entropy	0.278	0.155	0.243	0.243	0.172	0.231	0.167	0.200
Higuchi Fractal Dimension	0.140	0.208	0.119	0.119	0.122	0.141	0.071	0.114
Katz Fractal Dimension	0.176	0.128	0.085	0.085	0.182	0.230	0.151	0.222
Permutation Entropy	0.215	0.218	0.283	0.283	0.119	0.082	0.077	0.079
Sample Entropy	0.259	0.166	0.178	0.178	0.177	0.224	0.190	0.210
Spectral Entropy	0.136	0.196	0.157	0.157	0.174	0.133	0.119	0.278

Complexity features having different distributions in Cognitive Disequilibrium & Flow

Random Forest results trained using embeddings as features:

- Average five fold leave-one-subject-out accuracy **68.36%**
- Average 80/20 random split accuracy **81.42%**

Lessons: (1) *With some training on subjects the model better distinguishes between flow and disequilibrium (CD)* (2) Flow & CD differ significantly in terms of time series complexity

Research questions & highlights

Lessons from prior work: Cognitive state influences **gross-body movements** [2]

Limitations:

- Intrusive & expensive sensors
- Culturally insensitive features that violate privacy

Research question: *Can we predict cognitive states using patterns in head and eye movements?*

Cognitive states of interest: *Cognitive Disequilibrium (CD), Flow state*

Q1: *Do measures of time series complexity differ between states of CD and flow?*

Inspiration: Fluctuations in gross body movements undergo whitening when individuals experience CD [2]

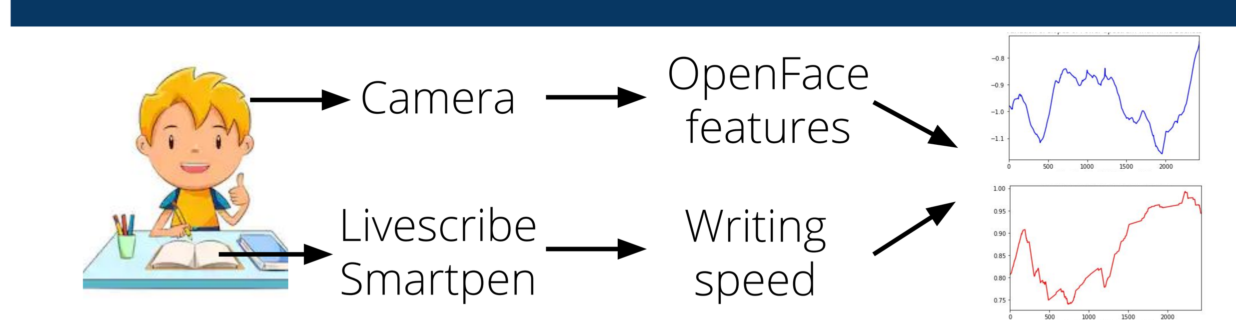
Q2: *Can features extracted from unsupervised methods predict cognitive states of students?*

Inspiration: Existing affective computing research relies on expensive labelled data from trained experts

Future Work

Q3: *Do measures of time series complexity differ between states of cognitive disequilibrium and flow?*

Data

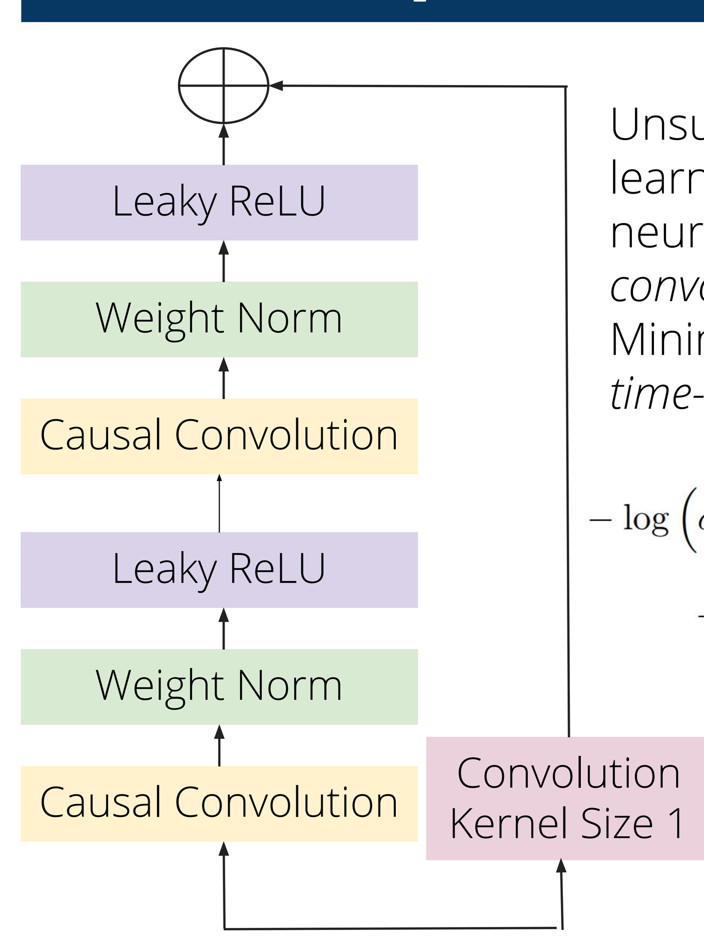


Seven 8 - 12 year old children [1]

36 sessions of children solving math puzzles having an average duration of 7.9 minutes per session

Source:
https://www.google.com/url?sa=i&source=images&cd=&ved=2ahUKEwi7pJO76f7jAhWsnOAKHfNSCBUQjRx6BAgBEAQ&url=https%3A%2F%2Fwww.shutterstock.com%2Fsearch%2Fstudy%2Bcartoon&psig=AOvVaw0cjt4kX19xVpgbgP7UZlRS&ust=1565748942386817

Unsupervised Model



Unsupervised representation learning using convolutional neural network with *causal dilated convolutions*

Minimized *triplet loss* with *time-based negative sampling:*

$$-\log\left(\sigma\left(\boldsymbol{f}(\boldsymbol{x}^{\mathrm{ref}},\boldsymbol{\theta})^{\top}\boldsymbol{f}(\boldsymbol{x}^{\mathrm{pos}},\boldsymbol{\theta})\right)\right) - \sum_{k=1}\log\left(\sigma\left(-\boldsymbol{f}(\boldsymbol{x}^{\mathrm{ref}},\boldsymbol{\theta})^{\top}\boldsymbol{f}(\boldsymbol{x}_k^{\mathrm{neg}},\boldsymbol{\theta})\right)\right)$$

References

[1] Chen, L., Gjekmarkaj, E., & Dubrawski, A. (2019). Parent as a companion for solving challenging math problems: Insights from multi-modal observational data

[2] D'Mello, S., Dale, R., & Graesser, A. (2012). Disequilibrium in the mind, disharmony in the body. Cognition & emotion, 26(2), 362-374.

[3] Franceschi, J. Y., Dieuleveut, A., & Jaggi, M. (2019). Unsupervised Scalable Representation Learning for Multivariate Time Series. arXiv preprint arXiv:1901.10738.

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