Project idea 1: *Review of the treatment of psychological constructs in machine learning for emotion recognition.*

Machine learning researchers have developed a number of systems to recognize and predict affective states like **mood** (Huang, Cao, Yu, Wang, & Leow, 2018; Jaques, Taylor, Sano, & Picard, 2017), **emotion** (Alm, Roth, & Sproat, 2005; Kosti, Alvarez, Recasens, & Lapedriza, 2017; Vielzeuf, Kervadec, Pateux, & Jurie, 2019), **sentiment** (Boiy & Moens, 2009; Pang, Lee, & Vaithyanathan, 2002; Tripathy, Agrawal, & Rath, 2016), **pain** (Ashraf et al., 2009; Littlewort, Bartlett, & Lee, 2007), and **wellbeing** (Jaques, Taylor, Sano, & Picard, n.d.; Wilckens & Hall, 2015). Many published articles briefly glance over the psychological literature on a given construct, often prioritizing practicality (i.e., what is easier to measure) and/or popularity (i.e., what others have done in the past) on their construct selection. Although a precise operationalization and measurement of psychological construct may not be a priority of machine learning researchers, their choices have important consequences in the **scientific landscape in affective computing** (i.e., what concrete advances have been done in affective state recognition and prediction); in **practical applications** in fields like health, education, finance, employee evaluation, customer satisfaction, etc.; and the **public perception** of the advances in machine learning and artificial intelligence. Hence, having a conceptual overview of the current state of the treatment of psychological constructs in machine learning research can help on multiple manners, for instance: (1) providing machine learning researchers with a more **in-depth source of guidance when selecting psychological constructs** as research targets; (2) informing affective scientist about the **current state of machine learning and artificial intelligence system on recognition and prediction of human affective states**; (3) providing a source of **inspiration for potential cross-discipline collaboration** between machine learning researcher and affective scientist; (4) **guiding practitioners in the private and public sector** interested in applying modern advances in affective computing, by identifying what can and can not be done with the available technology.

Project idea 2: *Learning continuous representations of emotion expression by training neural networks on categorical representations of emotion (and vice-versa).*

The nature of the psychological representation of emotion has been an issue of considerable debate for decades in the psychological literature (Barrett, 2006; Barrett, Adolphs, Marsella, Martinez, & Pollak, 2019; Cordaro et al., 2018; Keltner, Sauter, Tracy, & Cowen, 2019). One of the key points of disagreement, is whether emotion should be represented as a **discrete and self-encapsulated entity** (e.g., happy, sad, angry, etc), or as a **continuous entity constructed as the combination of some number of dimensions in abstract vector space** (e.g., relatively high or relatively low levels of arousal). The former perspective has been associated with the **basic emotion theory** championed by Paul Ekman and colleagues (Ekman & Keltner, 1997), whereas the latter has associated with the **circumplex model of emotion** proposed by James A. Russell and Mehrabian (Russell, 2003; Russell & Mehrabian, 1977). In the machine learning literature, the basic emotion theory perspective has dominated the research landscape framed as supervised classification problem (Rouast, Adam, & Chiong, 2019), yet efforts to incorporate the continuous-dimensional perspective has been done in recent years (Kervadec, Vielzeuf, Pateux, Lechervy, & Jurie, 2018; Kollias et al., 2019; Vielzeuf et al., 2019).

In a recent study, Vielzeuf and colleagues (Vielzeuf et al., 2019) trained a convolutional neural network to classify emotion in discrete categories, but used the **intermediate representations learned by the network to map emotion categories into a 3-dimensional continuous space**, namely, arousal, valence, and dominance. These results raise a series of interesting questions for the emotion representation debate: if **continuous representations** of emotion can be obtained from a neural network trained on **discrete representations** of emotion, to what extent discrete and continuous representation of emotion can be disentangled? Are discrete representations an "emergent" manifestation of the combination of continuous cognitive representations? Or are continuous representations just an artifact of the neural network architecture of choice? Or maybe an artifact from the dataset? One important limitation of the aforementioned study is that the model was trained using only seven emotional categories, namely: *neutral, sad, angry, happy, surprise, fear, and disgust*. Furthermore, the authors did not performed the opposite transformation: training a neural network on continuous representations and trying to extract discrete representations.

As a first step to both confirm and extend this line of research, we propose the following: (1) to replicate Vielzeuf and colleagues results with the same dataset; (2) to train a neural network on continuous representations and trying to extract discrete representations; (3) to use the EMOTIC (Emotion in Context) (Kosti et al., 2017) dataset to repeat the previous analysis. The EMOTIC dataset has a number of important advantages: (i) contains annotations for 26 categorical of emotion (instead of seven); (ii) contains annotations for the 3 dimensional model of *arousal*, *valence*, and *dominance*. The dataset used by Vielzeuf and colleagues only contained annotations for arousal and valence, and the dominance dimension was essentially inferred by the authors; (iii) contains annotations for the ***context*** on which the image was produced. This last characteristic is of great value since one of the main limitations of most dataset of emotion expression available do not contain any information about context, and context is an essential part of emotion recognition for humans (Barrett, Mesquita, & Gendron, 2011).

Project idea 3: Deep Learning: A practical introduction with annotated Python code for Psychologist

Rosenbush and colleagues (Rosenbusch, Soldner, Evans, & Zeelenberg, 2019) wrote a guide on traditional machine learning in R for psychologist (with little theory), and Urban and Gates (Urban & Gates, 2019) wrote a premier on Deep learning theory for psychologist (with none code or practical guidance). It occurred to me that I could create a Deep Learning guide/premier combining (basic) theory and annotated code in Python for psychologist.

Project idea 4: *Data Visualization: A practical introduction with annotated Python code for Psychologist*

Basically the same idea as project 3, but in the visualization space. I have been learning and writing a lot of data visualization code in the last year, and I am preparing a talk on declarative data visualization on python using Altair (instead of matplotlib with is imperative a more verbose) for my Meetup. It occurred to me that there are common domain-specific data visualization task in psychology that could benefit from a premier/guide in modern tools for statistical graphics.

References:

Alm, C. O., Roth, D., & Sproat, R. (2005). Emotions from text: Machine learning for text-based emotion prediction. *Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing - HLT '05*, 579–586. https://doi.org/10.3115/1220575.1220648

Ashraf, A. B., Lucey, S., Cohn, J. F., Chen, T., Ambadar, Z., Prkachin, K. M., & Solomon, P. E. (2009). The painful face – Pain expression recognition using active appearance models. *Image and Vision Computing*, *27*(12), 1788–1796. https://doi.org/10.1016/j.imavis.2009.05.007

Barrett, L. F. (2006). Are Emotions Natural Kinds? *Perspectives on Psychological Science*, *1*(1), 28–58. https://doi.org/10.1111/j.1745-6916.2006.00003.x

Barrett, L. F., Adolphs, R., Marsella, S., Martinez, A. M., & Pollak, S. D. (2019). Emotional Expressions Reconsidered: Challenges to Inferring Emotion From Human Facial Movements. *Psychological Science in the Public Interest*, *20*(1), 1–68. https://doi.org/10.1177/1529100619832930

Barrett, L. F., Mesquita, B., & Gendron, M. (2011). Context in Emotion Perception. *Current Directions in Psychological Science*, *20*(5), 286–290. https://doi.org/10.1177/0963721411422522

Boiy, E., & Moens, M.-F. (2009). A machine learning approach to sentiment analysis in multilingual Web texts. *Information Retrieval*, *12*(5), 526–558. https://doi.org/10.1007/s10791-008-9070-z

Cordaro, D. T., Sun, R., Keltner, D., Kamble, S., Huddar, N., & McNeil, G. (2018). Universals and cultural variations in 22 emotional expressions across five cultures. *Emotion*, *18*(1), 75–93.

https://doi.org/10.1037/emo0000302

Ekman, P., & Keltner, D. (1997). Universal facial expressions of emotion. *Segerstrale U, P. Molnar P, Eds. Nonverbal Communication: Where Nature Meets Culture*, 27–46.

Jaques, N., Taylor, S., Sano, A., & Picard, R. (n.d.). *Multi-task, Multi-Kernel Learning for Estimating Individual Wellbeing*. 7.

Keltner, D., Sauter, D., Tracy, J., & Cowen, A. (2019). Emotional Expression: Advances in Basic Emotion Theory. *Journal of Nonverbal Behavior*, *43*(2), 133–160. https://doi.org/10.1007/s10919-019-00293-3

Kervadec, C., Vielzeuf, V., Pateux, S., Lechervy, A., & Jurie, F. (2018). CAKE: Compact and Accurate K-dimensional representation of Emotion. *ArXiv:1807.11215 [Cs]*. Retrieved from http://arxiv.org/abs/1807.11215

Kollias, D., Tzirakis, P., Nicolaou, M. A., Papaioannou, A., Zhao, G., Schuller, B., … Zafeiriou, S. (2019). Deep Affect Prediction in-the-wild: Aff-Wild Database and Challenge, Deep Architectures, and Beyond. *International Journal of Computer Vision*, *127*(6–7), 907–929. https://doi.org/10.1007/s11263-019-01158-4

Kosti, R., Alvarez, J. M., Recasens, A., & Lapedriza, A. (2017). Emotion Recognition in Context. *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 1960–1968. https://doi.org/10.1109/CVPR.2017.212

Littlewort, G. C., Bartlett, M. S., & Lee, K. (2007). Faces of pain: Automated measurement of spontaneousallfacial expressions of genuine and posed pain. *Proceedings of the Ninth International Conference on Multimodal Interfaces - ICMI '07*, 15. https://doi.org/10.1145/1322192.1322198

Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up? Sentiment Classification using Machine Learning Techniques. *ArXiv:Cs/0205070*. Retrieved from http://arxiv.org/abs/cs/0205070

Rosenbusch, H., Soldner, F., Evans, A. M., & Zeelenberg, M. (2019). *Supervised machine learning methods in psychology: A practical introduction with annotated R code* [Preprint]. https://doi.org/10.31234/osf.io/s72vu

Rouast, P. V., Adam, M., & Chiong, R. (2019). Deep Learning for Human Affect Recognition: Insights and New Developments. *IEEE Transactions on Affective Computing*, 1–1. https://doi.org/10.1109/TAFFC.2018.2890471

Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological Review*, *110*(1), 145–172. https://doi.org/10.1037/0033-295X.110.1.145

Russell, J. A., & Mehrabian, A. (1977). Evidence for a three-factor theory of emotions. *Journal of Research in Personality*, *11*(3), 273–294. https://doi.org/10.1016/0092-6566(77)90037-X

Tripathy, A., Agrawal, A., & Rath, S. K. (2016). Classification of sentiment reviews using n-gram machine learning approach. *Expert Systems with Applications*, *57*, 117–126. https://doi.org/10.1016/j.eswa.2016.03.028

Urban, C., & Gates, K. (2019). *Deep Learning: A Primer for Psychologists* [Preprint]. https://doi.org/10.31234/osf.io/4q8na

Vielzeuf, V., Kervadec, C., Pateux, S., & Jurie, F. (2019). The Many Variations of Emotion. *2019 14th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2019)*, 1–7. https://doi.org/10.1109/FG.2019.8756560

Wilckens, M., & Hall, M. (2015). Can Well-Being Be Predicted? A Machine Learning Approach. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2562051