Critique 2 | Week 2 | Disha Singh

The oldest of these articles about *Calorific expenditure estimatio*n(2009) takes me to the time when smart phones were beginning to appear in the market. It must have been a brilliant idea then, when Fitbits were unheard of, to start using sensors within smart phones for tackling the problem of obesity and many related health issues just by tracking food calories. Realizing that the gap lies in the issue that people overestimate their exercise and underestimate how much they eat and that just showing the people clearly their net calorie intake can be the first step for cure must have been exciting. Due to the limited battery life of cell phones though, sensors were underutilized in these devices. Although in 2014, when we had much powerful phones, the *Fusion of motion sensors* 2014 article still talks about having to use less computationally & storage expensive features to conserve battery life. However, something I want to have discussed in class is the opinion I have that the very foundation of this article is weak. First, complex models are not used to find step counts etc., *so that the researchers that will use the approach presented in this paper can better understand what they are doing*. Should the focus be on creating reliable, strong studies or something people understand like superstition? Third, I feel if the study is difficult, only more learned researchers will anyway take it up but the product will be qualified more. Second, the authors' opinion about a system they have used from related work is, "*We don't know how accurate these systems are.*" How can anyone else build upon/reuse research that is not build on confident grounds? Also, even though the authors mention that there were 51 participants, they do mention that some people could not complete the exercises, which concerns me that actual data samples were much lesser. If instead of preventing, the data collectors had allowed people with health issues to participate in the study, I believe that the results would be more catered to the audience who actually need such technology. In addition, instead of keeping the order of activities same for all the people, if it was different, this transitional feature would make the study more real world relevant. The sample collection of 51 people in this study though is much more diverse by age, gender, body types and thus more unbiased for the algorithms than the 2014 study where only 10 people are taken and those too all males, age 25-30, without mentioning any reference to their body types! The samples in any ML study must be all independent and randomly collected and must represent the real world data but here, it is too small and dependent. The 2009 study however, has fewer activities (treadmill lab test and a routine field test) than the 2014 one where every person has 5 devices attached on different positions and has a wide range of activities to do. The point that features selected in 2014 study were bottle necked on the computational and storage capacity provokes that capturing complex features in future when the mobile phones are much robust will see more innovation within the fusion of sensors realm. Something I learnt from this article is that since performance of each sensor is a function of many variables like activity, placement on body, classifiers used, it is hard to comment on their accuracy as such. But given restrictions on these factors, we can definitely find which combination of sensors works best. Fast forward to 2019, the "*Self supervised learning*" article shows how much we have advanced in just a couple years, how the problem today is not collection of data, but to tag 100s of terabytes of unlabeled sensor data available – solved by unsupervised deep learning techniques for pre-training ML models which does not need the training data to be classified into activities. The models then only needs task-specific fine tuning with small labelled activity dataset for HAR which is both cost and time effective.