

Rise of the Video Selfie

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1. ABSTRACT

In the past few years we witnessed the rise of the *Selfie* phenomena. The world of online social networks was taken by a storm. There were several social, psychological and social computing studies trying to understand this phenomena. In late 2012, a company was found on the basis of adding a new dimension to the concept of social media called Vine. Vine was solely based on the premise of sharing a short high impact video that delivers a message. Soon the service became popular and the bigger and more popular services like Instagram and Twitter started following their footsteps. They have now enabled sharing of limited duration video clips. Our paper tries to measure this phenomenon and makes certain studies about how a particular vine-like video gains popularity. We further look at this through the lens of affective computing and machine learning, and propose a new framework to understand human affects in the budding research field of social *Artificial Intelligence*. We do all this by collecting a 1 month long dataset of all the popular videos overall and amongst popular channels.

2. INTRODUCTION

Online social networks (OSNs) have seen a massive surge in usage over the past decade. The surge is going hand in hand with the explosion of smart phone industry. More and more social interactions are now driven by media contents like selfies, group selfies and videos because of the ubiquitous nature of cameras. A sharp change in cultural aspects of online social interactions are evident and have also been studied in detail in papers like [2]. With the rise of social media networks like Vine and Instagram, human to human non-verbal interactions have another dimension to manifest. One of the predominant modality of self expression arose from this boom in social media, and that was the Selfie. The [2] paper explores several of the properties of selfie amongst Instagram users, where they explore correlation of facial orientation, poses and smiles with parameters like country of origin of the selfie user, post frequency, likes received, number of faces in the pictures, gender and smile scores. Such studies give us interesting insights about the sharp rising OSN phenomena of selfies. The study also states that more than

50 percent of photos shared on Instagram, fall under the category of selfies.

A major change in these behaviours was seen when the social network called Vine was launched in 2012. Vine adds another dimension to the act of self expression, where the users can record a 7 second long video and post it online and get engagement from peers. This service got so popular that the larger services like Instagram and Twitter also added the feature of short videos to their services.

3. SENTIMENT ANALYSIS METHODS

To the best of our knowledge we have evaluated certain popular approaches in solving the problem of extracting latent sentiment in a media content. The sentiment analysis methods broadly fall into two bins. One is the Content based Image retrieval (CBIR) [?] set of approaches, which actually analyse the image structure and contents to extract features and inferences about the image. The second bin is emotional semantic image retrieval (ESIR) [?] which aim at trying to extract the semantic gist of a particular image. Human brain is great at extracting such semantics. For example it is very natural for a person to describe a particular image as "picturesque" or "scenic" or to describe someone's clothing as "tacky", "classy" or "elegant". These semantic classes, no matter how subjective, are also sufficiently descriptive for another human being to process. In the subsections to come, we will discuss some of the popular perceptual sentiment analysis methods.

3.1 Facial Action Coding System (FACS) based methods:

Facial Action Coding System (FACS) based approach towards understanding human affects was the pioneering research done at CMU that paved the way of modern affective computing. The paper [?] talks about this pioneering research. The method works on a very important base of Facial Action Coding [?] system which encodes movement of specific muscles of human face and encodes actions units as a combinations of one or more of these movements. These AUs or Action Units are then carefully measured from frontal images of faces and then models are built on top of these measurements to classify different emotions.

The paper evaluates these AU based methods for specific AUs. They do not show a very convincing performance analysis for the 7 prime emotion bins, but evaluate classification accuracy for each of the AUs. The performance shows very promising accuracy for detecting AUs in upper and lower part of the face. Works like [?] [?] take these concepts forward and use features in AU zones to build classifiers. These studies employ features like Pyramids of Histograms of Gradients (PHOG) and Local Phase Quantisation (LPQ) to classify across 5 key emotions of anger, fear, joy, relief

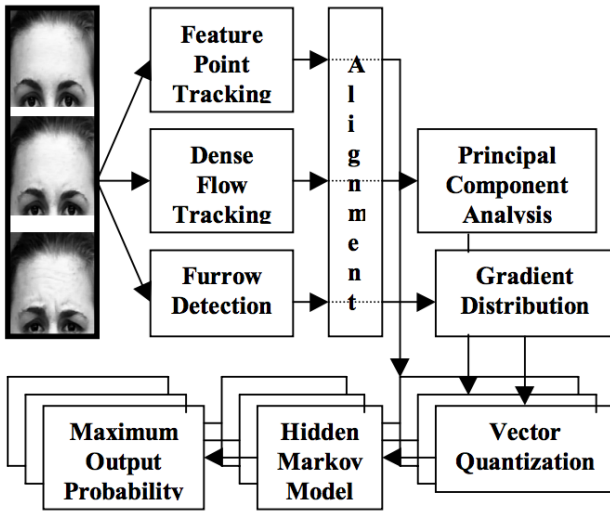


Figure 1: System architecture of FACS AU based Emotion recognition

and sadness. Their methods attain a very impressive performance bracket of 67 to 74 percent detection accuracy.

3.2 Semi-supervised learning models

Over the past two decades, with the surprising developments parallel computing and general purpose graphics processor computing, the space for scaling up and parallelising sparse computation has increased exponentially. This paved the way for extremely fast and scalable neural network frameworks.

4. REFERENCES

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