# Quantifying the Temporal Contingency of Protest Symbol Construction Processes: Visuality during the Anti-ELAB 2019 Protests

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## Extended Abstract

The protest movement behind the demonstrations taking place in Hong Kong during 2019, Anti-ELAB (Anti Extradition Law Amendment Bill), became infamous for using umbrellas, laser pointers and masks in collisions with the local authorities. In this paper, we trace how umbrellas, lasers and masks became central visual symbols of the Anti-ELAB movement, with a specific emphasis on the shifting meanings and practices associated with these objects throughout the protest period.

A growing sociological literature examines the visual expressions of social movements through symbols and images with a focus on embodied practices of protest (Doerr and Teune, 2013; Doerr et. al, 2013; Doerr and Milman, 2015; Kwok, 2021; Mattoni and Teune, 2014; Neumayer and Rossi, 2018; Pang, 2021). While this literature offers valuable insights into how visuality shapes collective identities and emotions, less attention is given to processes of symbol construction, and the shifting meanings and practices associated with prominent images and objects as social movements evolve. The Anti-ELAB movement represents a rich case for studying such processes, as a series of objects (umbrellas, lasers and masks) momentarily assumed symbolic status during the protest activities in Hong Kong.

We use methods from computational sociology (including dictionary classification, object detection, and temporal network analysis) and tweets about the 2019 Hong Kong protests (N = 1,615,832), to trace the provisional and unstable characteristics of the Anti-ELAB movement's visual expressions. Data was acquired via the official Twitter API, and tweets mentioning hashtags relevant to the protests in Hong Kong were collected. Using Gensim's Word2Vec.most_similar functionality, we constructed dictionaries for umbrellas, lasers and masks and created object-specific datasets using the dictionaries as classifiers. All tweet images were downloaded (N = 671,164) and the YOLOv4 object identifier (Figure 1) was used to detect umbrellas in all images over time (Figure 2). Temporal ego networks were used to trace object associations in tweet texts over time, and to interpret the shifting meanings and practices related to each object (Figure 3). Lastly, drawing on Carlsen's (2019) quali-quant strategy, we adopted a mixed methods approach by oscillating between qualitative and quantitative modes of analysis. This approach allowed us to 'test' our interpretations across domains, i.e., testing whether interpretations based on quantitative results could be validated through qualitative insights and vice versa.

Theoretically, we draw on actor-network theory (ANT), and analyse objects and technologies as nonhuman actants with agency just like humans (Callon and Latour, 1981; Latour, 1993). With a specific focus on translation processes, we follow the actants (umbrellas, lasers and masks), describing their situational and dynamic character as they oscillate between practical-confrontational translations (e.g. as weapons or shields in collisions with authorities) and more symbolic-visual translations (e.g. as symbols that visualize collective resistance) during the Hong Kong protests.

Results show that tweets mentioning either umbrellas, lasers or masks receive significantly more likes, retweets, and are more likely to contain images (Figure 4). Further, the three actants oscillate between symbolic-visual and practical-confrontative translations during the demonstration period. Symbolic-visual translations are shown to be temporally contingent, as they relate to specific events happening on the ground in Hong Kong that are often related to (counter-)surveillance. Further, the actants replace each other as the primary protest symbol over time, as the object previously functioning as the key symbol is translated into a practical-confrontative translation, as another object takes on a symbolic-visual translation. However, the mask ultimately keeps its symbolic-visual translation for a longer period.

From our results, we define a novel concept of *momentary symbols*: symbols that for a shorter period rapidly grow into a dominant symbol for the movement, but just as quickly acquire a less central symbolic role in the protest movement. Momentary symbols are characterized by a high degree of acceleration and deceleration in terms of activity and symbolic translations, which may characterize the symbol construction process of contemporary protest movements. Our study adds to the scholarship on visuality and social movements by demonstrating the relevance of using processual and temporal approaches to capture the erratic and volatile nature of visual expressions in social protests. Further, we provide an analytical framework that allows for quantifying protest movements' temporally contingent symbol construction processes via communication platforms.

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Figure 1. Two images from the dataset containing umbrella(s). The left image is from April 30th, 2019, and shows protesters marching holding umbrellas (a symbolic-visual translation). The object detection pools a large area of many umbrellas into one, suggesting the estimate on the count of umbrellas in the image is conservative. The right image is from November 17th, 2019, showing teargas and a protester holding one umbrella (a practical-confrontative translation).

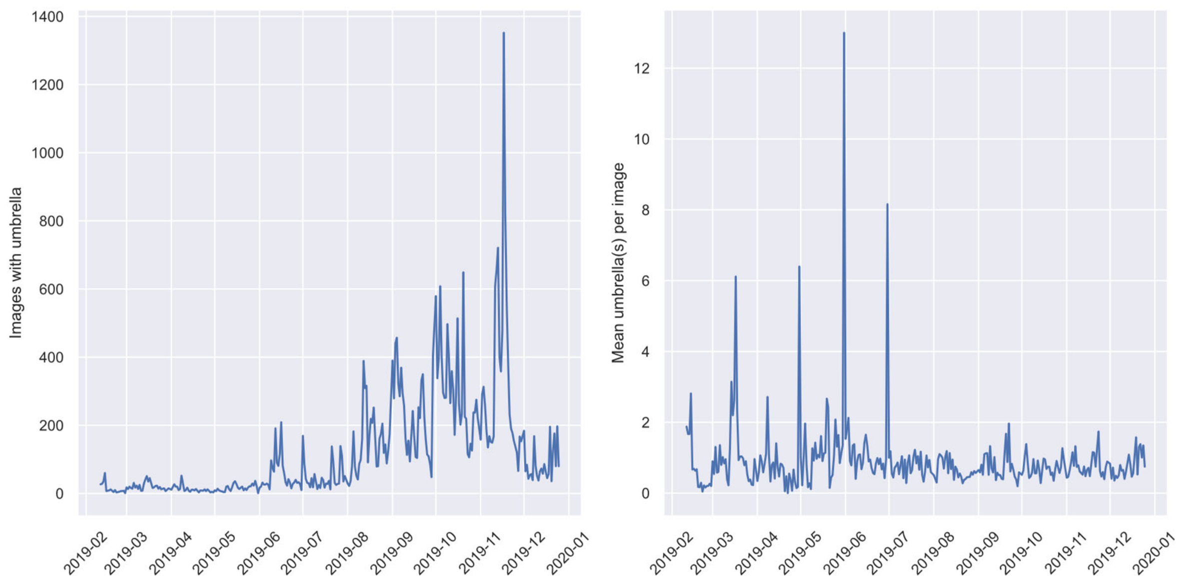


Figure 2. Daily counts of images containing umbrella(s) (left) (n=37,005) and mean umbrellas per image per day (right) (N=671,164). YOLOv4 object detector used to identify umbrellas in images. Only umbrella detections with confidence scores above 0.5 are counted as a match.

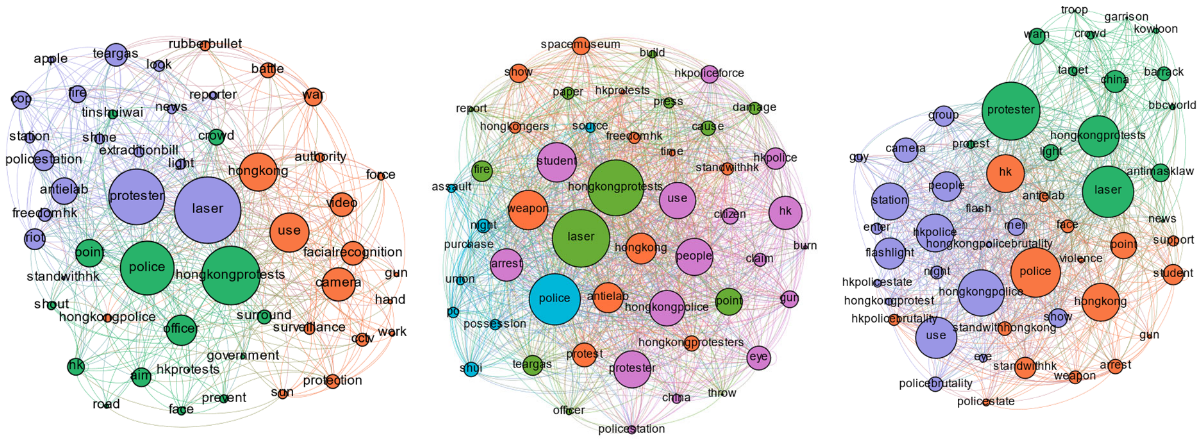

Figure 3. Three ego networks for the laser actant at different time points. On the left for period 1 (2019-07-25 – 2019-08-05), in the middle for period 2 (2019-08-06 – 2019-08-22), and on the right for period 3 (2019-10-25 – 2019-11-11). Node sizes denote degree centrality, and node color denotes cluster belongingness. All networks are visualized using the Force2Atlas algorithm in Gephi.

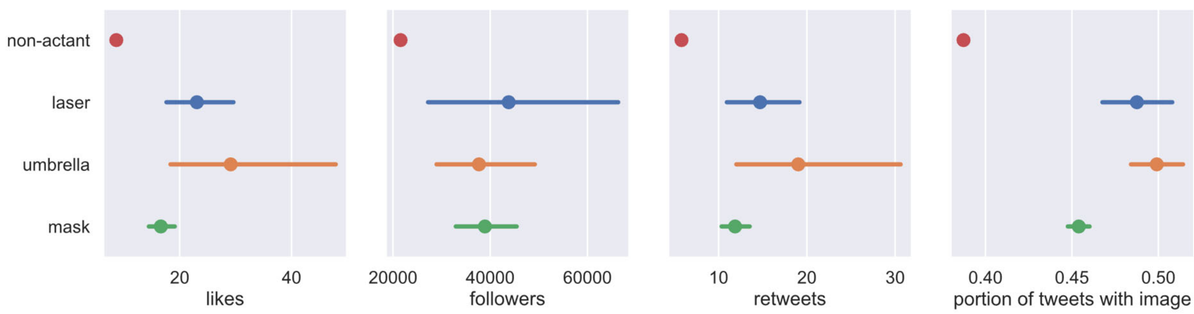


Figure 4. Forest plots with mean likes, followers, retweets and image associations for non-actant and actant samples. Errors bars indicate 99% confidence intervals drawn from 10.000 bootstrap samples. Z-tests ($p<0.000$) and Mann-Whitney U-tests ($p<0.000$) confirm statistically significant higher means and medians on all parameters for actant tweets compared to non-actant tweets.