Spatial analyses of social media event response. The focus of [7] is to detect events from photos on Flickr by exploiting the tags supplied by users. In particular, the temporal and locational distributions of tag usage are analyzed. The problem of event summarization using tweets is well faced by [6], where the authors argue that for some highly structured and recurring events, such as sports, it is better to use sophisticated techniques to summarize the relevant tweets via Hidden Markov Models. The paper [5], adding the information given by cell-phone traces, deals with the analysis of crowd mobility during special events. They show that the origins of people attending an event are strongly correlated to the type of event. Finally, [1] proposes a procedure consisting of a first collection phase of social network messages, a subsequent user query selection, and finally a clustering phase, for performing a geographic and temporal exploration of a collection of items, in order to reveal and map their latent spatio-temporal structure. Specifically, both several geo-temporal distance measures and a density-based geo-temporal clustering algorithm are proposed. The paper aims at discovering the spatio-temporal periodic and non-periodic characteristics of events occurring in specific geographic areas.

Social Media Analysis for Fashion. The work [13] presents a qualitative analysis on the influence of social media platforms on different behaviors of fashion brand marketing. They analyze their styles and strategies of advertisement. The authors employ both linguistic and computer vision techniques. The study [12] sets out to identify attributes of social media marketing (SMM) activities and examines the relationships among those perceived activities, value equity, relationship equity, brand equity, customer equity, and purchase intention through a structural equation model. The findings of [9] show that different drivers influence the number of likes and the number of comments to fashion posts. Namely, vivid and interactive brand post characteristics enhance the number of likes. The analysis in [8] shows that many of the tweets during a 2011 Victoria's Secret Fashion Show were discussing the social status of the fashion models. The article [10] examines the London Fashion Week (LFW), arguing that this event effectively represents the field of fashion, as it shows the boundaries, relational positions, capital and habitus at play in the field. Finally, [14] develops a motion capture system using two cameras that is capable of estimating a constrained set of human postures in real time. They first obtain a 3D shape model of a person to be tracked and create a posture dictionary consisting of many posture examples.

6. CONCLUSIONS

We discussed how social content responds to live events in function of space, focusing on the Milano Fashion Week. We demonstrated that brands can be clustered into 4 classes of increasingly far-reaching responses, from most concentrated ones to most dispersed ones; we also showed that brand popularity alone is not sufficient for explaining dispersion. Our future work is to build a predictive model of the spacial dynamics of social content, and also attempt to correlate spreading with other features beyond brand popularity, e.g. by studying the profiles of each brand's social networks and specifically of Instagram. We also would like to understand better

7. ACKNOWLEDGMENTS

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