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From Paris to Berlin: Discovering Fashion Style Influences Around the World Supplementary Material

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In this supplementary material, we provide additional results of our fashion influence discovery model and the naive baselines details.

Fashion styles Fig. 1 shows more examples of the fashion styles learned by our style model from the GeoStyle dataset; a large-scale dataset of Instagram and Flickr images collected from 44 major cities around the world. A style is a combination of certain attributes describing materials, colors, cut, and other factors, such as *V-neck, red, formal dress*. Some of the learned fashion styles may reflect a season related type of garments (*e.g.* the yellow jacket and scarf style) or a local traditional or cultural clothing (*e.g.* Fig. 1 upper left row); however, many of the learned styles are common across different countries and cultures.

City → World influence Fig. 2 shows the influence exerted by American (top) and European (bottom) cities on a set of learned fashion styles. The figure reveals that some cities act as the main players and dominate the influence relation for the global trend of a fashion style, for example Chicago & Style S_7 and Sofia & Style S_{16}. However, for few styles (like S_9 and S_{12}) the influence pattern is dispersed across multiple players.

City → City influence In Fig. 3, we show the pairwise fashion influence relations discovered by our model on cities from the North and South American continents. New York City is a major fashion influencer among the American cities and Vancouver exerts and receives fashion influence at a high volume indicating that it is an important fashion

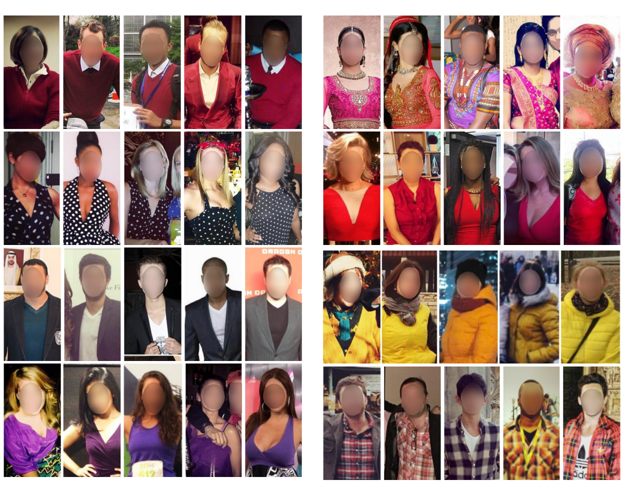
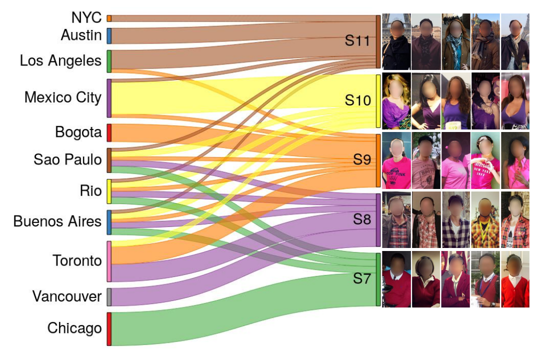
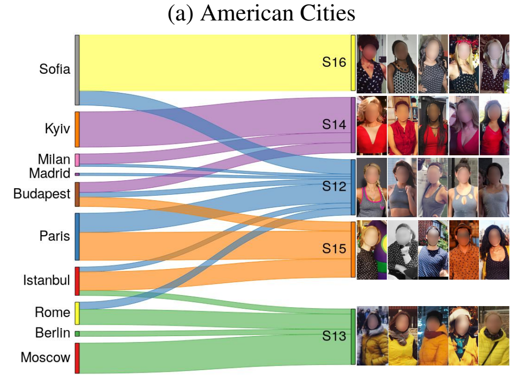


Figure 1: Examples of the learned fashion styles from a large-scale dataset of Instagram and Flickr images.

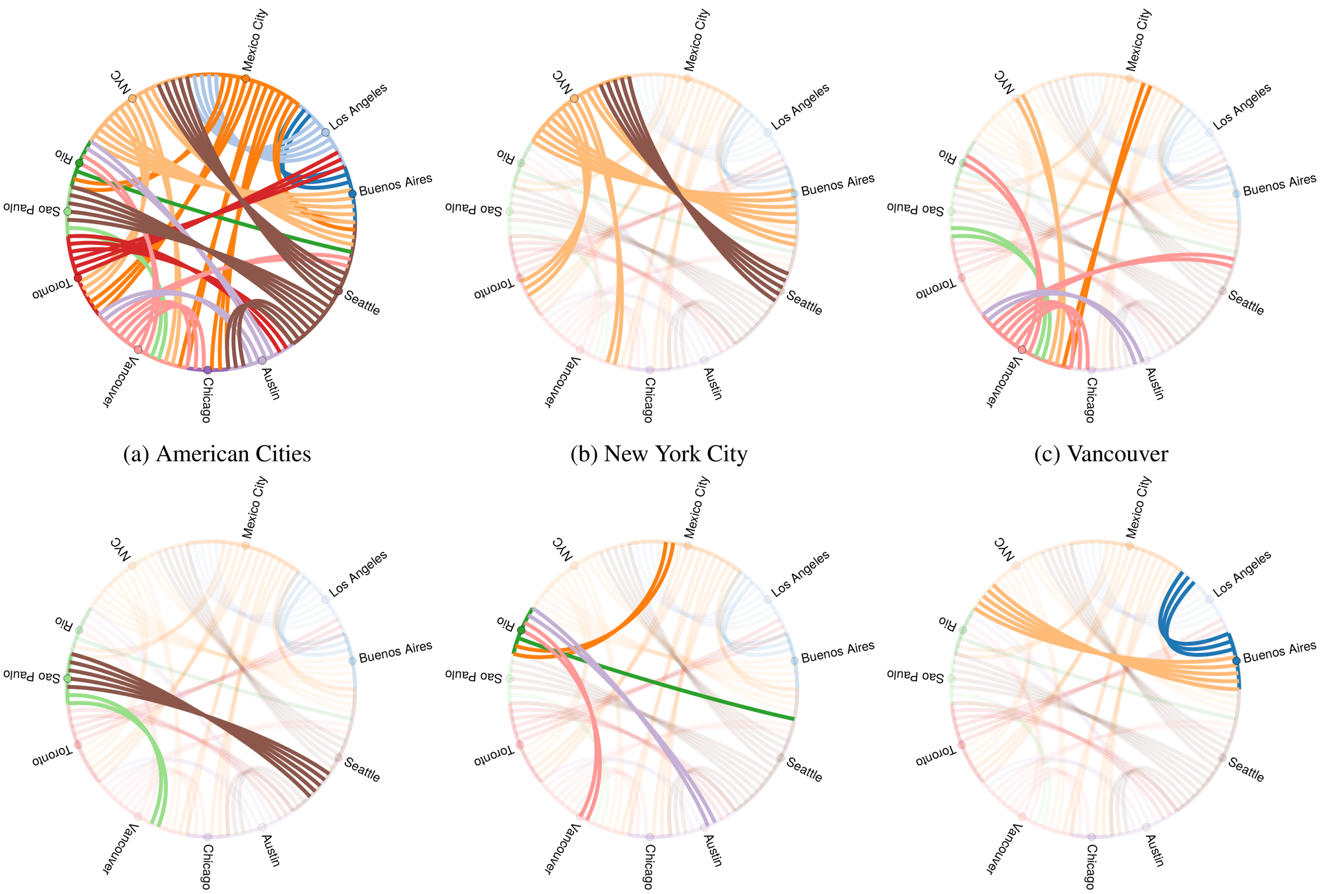


(a) American Cities



(b) European Cities

Figure 2: Our model infers the fashion influence exerted by different cities on the global style trends, as seen here for (a) American and (b) European cities.



(a) American Cities (b) New York City (c) Vancouver

(d) Sao Paulo (e) Rio de Janeiro (f) Buenos Aires

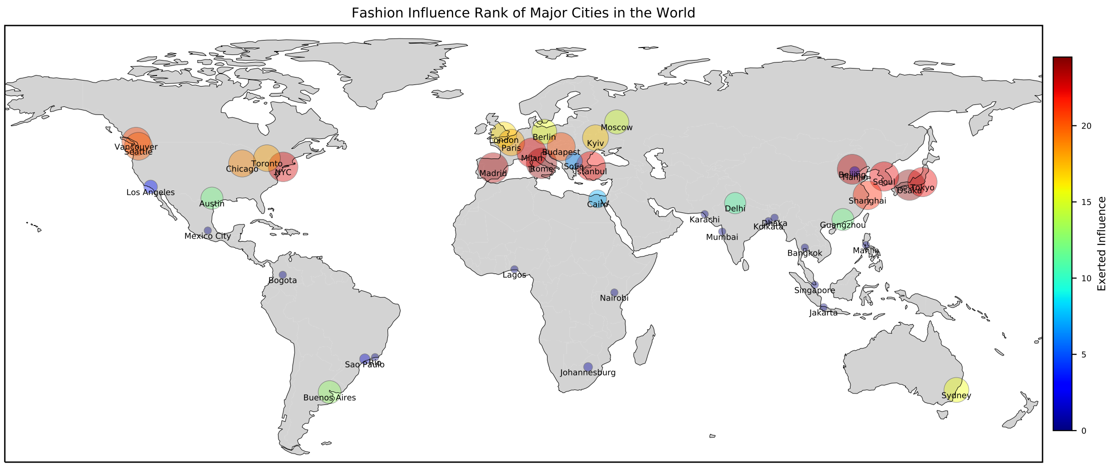
Figure 3: Style influence relations discovered by our model among cities in North and South America (top and bottom, respectively). The number of chords coming out of a node (*i.e.* a city) is relative to the influence weight of that city on the receiver. Chords are colored according to the source node color, *i.e.* the influencer. Our model reveals interesting influence patterns, like the major fashion influencer (*e.g.* New York City), the fashion hub (*e.g.* Vancouver), and the single- or multi-source fashion receiver (*e.g.* Buenos Aires and Rio de Janeiro, respectively).

hub. Other cities draw fashion influence from a main source (*e.g.* Buenos Aires and Sao Paulo) or from a diverse set of influencer (*e.g.* Rio de Janeiro).

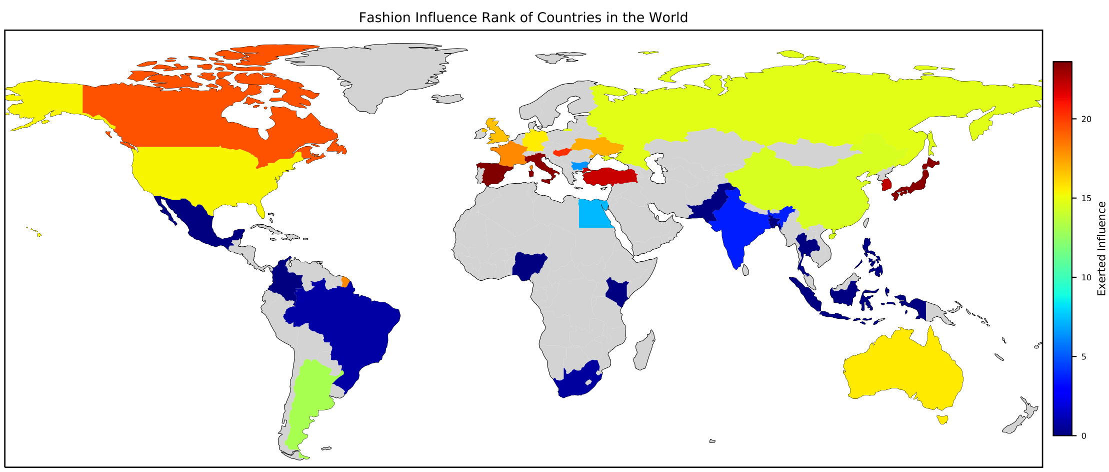
A world view of fashion influence Finally, in Fig. 4 we provide a global view of fashion influence on the world map. Fig. 4a reinforces our previous observation from the correlation analysis with cities meta information (Section 4.3 in the main paper). Most of the influential cities lay in the northern hemisphere and specifically in its upper part, which also explains the positive correlation of the fashion influence rank with latitude and colder temperatures. In Fig. 4b and Fig. 4c, we show the influence score inferred by our model when aggregated by country and continent, respectively. While at the country level we see that some Asian and American countries have high fashion influence scores (*e.g.* Japan and Canada), at the continent level Europe still leads in terms of global fashion influence.

Naive models In our forecast experiments, we consider five naive baselines that rely on basic statistical properties of the trajectory to produce a forecast:

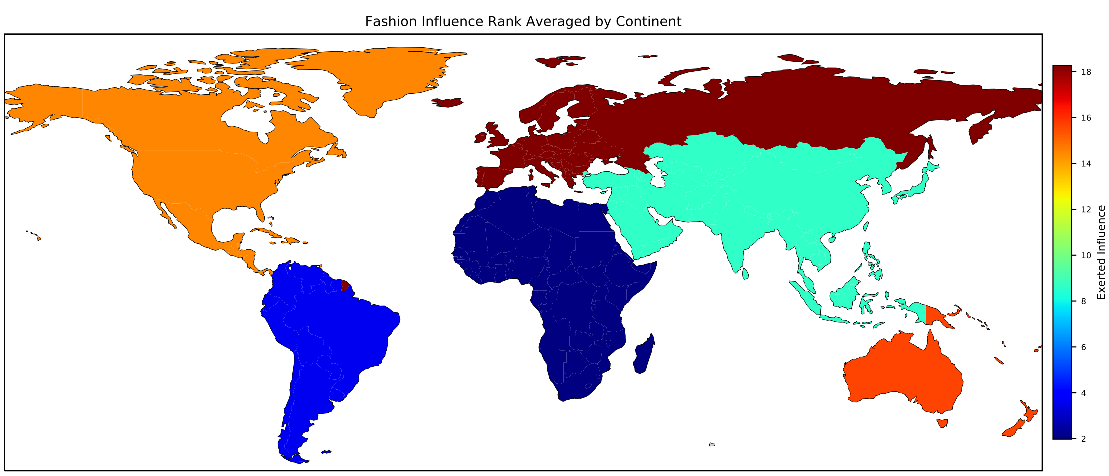
- Gaussian: this model fits a Gaussian distribution based on the mean and standard deviation of the trajectory and forecasts by sampling from the distribution.
- Seasonal: this model forecasts the next step to be similar to the observed value one season before $y_{t+1} = y_{t-season}$. We set a yearly season of 52 weeks.
- Mean: it forecasts the next step to be equal to the mean observed values $y_{t+1} = \text{mean}(y_1, \dots, y_t)$.
- Last: it uses the value at the last temporal step to forecast the next $y_{t+1} = y_t$.
- Drift: it forecasts the next steps along the line that fits the first and last observations.



(a) Major Cities



(b) Countries



(c) Continents

Figure 4: Fashion influence scores as inferred by our model from everyday images of people around the world at (a) the city, (b) the country, and (c) the continent level. Areas shaded with a gray color are ones without visual observations, consequently with no fashion influence estimates.