

Supplementary Material for: “GeoStyle: Discovering Fashion Trends and Events”

In Section 1 we describe the reasoning we did when choosing the parameter values for the grouping cost function. Section 2 shows the results of in-sample predictions of our method vs. other baselines. In Section 3 we show the results of running our framework on pairwise combinations of attributes. In Section 4 we show the performance of our framework on long-range prediction. Section 5 extends the interpretability example we show in the main paper. Section 6 presents the top-100 events discovered by attribute-trend based event detection and style-trend based event detection. Section 7 presents the topmost style-trend based events for each city. Finally, in Section 8 we show some of the results for trend fitting and prediction.

1. Parameter values for grouping cost function

We set $d_{\max} = 5$, as the Lunisolar calendar can drift a maximum of five weeks away from the Solar calendar[1].

We arrived at the value of δ_{\max} as follows. We experimented with a range of values for δ_{\max} , from $1 \cdots 5$. We give a grouping with $\delta_{\max} = k$ an improvement score s , if it was able to group an extra s events compared to when $\delta_{\max} = k - 1$.

We found the value s by finding events consisting of a pair of weeks which are not grouped when $\delta_{\max} = k - 1$ and grouped when $\delta_{\max} = k$. Out of these sets of pair of weeks we find the pairs with non-zero intersection in the top-5 keywords. Note that this keyword matching is an approximation of s score because there is a possibility that no keyword matches even though both outliers are caused by the same event. After $\delta_{\max} = 2$, s drops to zero. Hence, we chose $\delta_{\max} = 2$, allowing only consecutive weeks to be grouped together.

We decided upon b and c in the following way. b, c affect the ordering of grouped events vs singleton events. Since singleton events (say e_s) will have a value of $C_T(e_s) = 1$ and for grouped events (say e_g) this value is < 1 , even with $\bar{v}_{e_s} = \bar{v}_{e_g}$ the grouped event will be more salient. As b, c values increase, the slope of the linear functions decreases, and the saliency of grouped events decreases relative to singleton event. So we choose a large value for b and c . We choose $c = 18$ and $b = 15$, which are large enough to not change the ordering with the increment.

Fit function	MAE	MAPE
	$\sum_t f(t) - T(t) $	$\sum_t \frac{ f(t) - T(t) }{T(t)}$
linear	0.0282	21.68
sinusoid	0.0152	15.71
sin+linear	0.0151	15.56
cyclic	0.0150	15.42
ours	0.0131	14.38

Table 1: Comparison of our fitting function against baselines by in-sample errors.

2. In-sample predictions for ours vs other baselines

Table 1 shows the in-sample performance of our method against other baselines for attribute trends. Not only does our method perform better than other baselines, the errors are not very far from the the out-of-sample errors. This shows that our method could forecast robustly for a longer range of time periods.

3. Trends and events with pairwise attributes

In addition to doing our analysis on the attributes and discovered styles, we run our pipeline on the pairwise combinations of attributes. Pairwise combination of attributes results in quadratically more computations with the number of attributes. 46 different attributes result in 1035 different pairwise combinations of these attributes. Since all these attribute combinations will not be equally popular (for example it is very unlikely that someone would wear a necktie with a dress) we do our analysis on top-200 most popular attribute combinations. For binary attributes, we only consider when the attribute has a positive value. For example, “wearing a suit with a necktie” is considered as a valid combination but “not wearing a scarf with a dress” is not considered.

Table 3 shows the performance of our trend-fitting method against the baseline methods on pairwise combinations of attributes. Our method beats the baselines in long-range forecast and is very very close to vector autoregression in short-range forecast. Table 2 shows the top five events detected by

Images City Attribute 1 Attribute 2 Month Keywords					
					
	Bangkok	Bangkok	Chicago	Bangkok	Moscow
	Yellow color	Short sleeve	Red color	No collar	Wearing hat
	Solid pattern	Yellow color	short sleeve	T-shirt	Outerwear
2014 Dec, 2015 Dec	2014 Dec, 2015 Dec	2014 Jun	2014 Apr	Jan 2014, Jan 2015, Jan 2016	
father, happy	dad, father	cup, stanleycup	songkran, festival	newyear, winter	

Table 2: Top five events detected across the world by finding anomalous behaviour in trends over pairwise attributes.

Model	Next week		Next 26 weeks	
	MAE	MAPE	MAE	MAPE
mean	0.0199	23.78	0.0324	58.04
last	0.0138	18.42	0.0309	49.81
AR	0.0140	18.09	0.0283	48.18
VAR	0.0109	16.44	0.0240	41.67
ES	0.0137	18.06	0.0308	49.87
linear	0.0295	27.52	0.0380	57.15
sinusoid	0.0133	16.96	0.0167	25.26
sin+lin	0.0134	17.09	0.0171	26.72
cyclic	0.0122	16.30	0.0187	27.91
Ours	0.0112	14.96	0.0146	23.12

Table 3: Comparison of our model against baselines for trends over pairwise attribute combinations.

Model	Next 52 weeks	
	MAE	MAPE
mean	0.0292	27.63
last	0.0325	29.44
AR	0.0234	23.46
VAR	0.0258	25.83
ES	0.0310	27.89
linear	0.0304	25.50
sinusoid	0.0175	18.33
sin+lin	0.0180	19.01
cyclic	0.0179	18.70
Ours	0.0164	17.79

Table 4: Comparison of our model against baselines for trends over next 52 weeks.

using pairwise attribute combinations. Major events detected by our pipeline on single attributes are also getting detected when combinations of attributes are used.

4. Long-term trend forecasting

Table 5 shows the performance of our method when predicting over a longer duration of time with our method. We forecast over the last 1 year, with models trained over first 2 years. Our method performs better when compared to all the baseline models.

5. Interpreting phase difference

As discussed in the main paper, the parameters of our model are interpretable and could be used to reveal insights. Since ϕ models the phase of cyclical spikes and $\text{sgn}(m_{\text{cyc}})$ (sign of m_{cyc}) models whether the spikes are upward or downward-facing. $\text{sgn}(m_{\text{cyc}})\pi + \phi$ can be interpreted as

the metric modeling where the maxima occur annually for a trend. Figure 5 in the main paper only looked at cities with *positive* spikes. We extend that analysis now to all 44 cities using absolute difference in $\text{sgn}(m_{\text{cyc}})\pi + \phi$ instead. Figure 1 shows the pairwise absolute difference between this metric for all 44 cities for wearing multiple layers. Because multiple layers are worn usually during winters, cities in each hemisphere form a cluster amongst themselves.

6. Top 200 events sorted by saliency

Table 6 and 7 show the top 100 events discovered by our method across the worlds using attribute-trends and style-trends respectively. We show the top-5 words associated with the events instead of top-2 (unlike the main paper), as reasons for some events with lower saliency could be found in top-5 keywords but not in top-2.

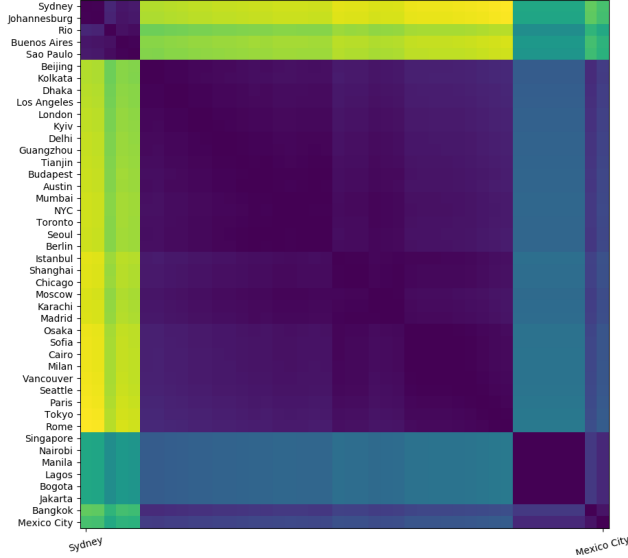


Figure 1: Pairwise difference for the multiple-layered attribute between 44 cities, using the metric $\text{sgn}(m_{\text{cyc}})\pi + \phi$.

Model	Next 52 weeks	
	MAE	MAPE
mean	0.0292	27.63
last	0.0325	29.44
AR	0.0234	23.46
VAR	0.0258	25.83
ES	0.0310	27.89
linear	0.0304	25.50
sinusoid	0.0175	18.33
sin+lin	0.0180	19.01
cyclic	0.0179	18.70
Ours	0.0164	17.79

Table 5: Comparison of our model against baselines for trends over next 52 weeks.

7. Events discovered for each city by style-trends

Figure 2,3,4 and 5 show the major events with most descriptive keywords for all the cities (Except Lagos, Johannesburg, Nairobi and Sydney, which are shown in the main paper). The styles successfully capture the combinations of attributes for example, jackets without ties in Seoul and jackets with ties in Tokyo. Another thing to note is that in places like Milan and Jakarta people are not dressing according to what they would conventionally wear during Thanksgiving or Christmas respectively. Instead, people go out more during these festivals and wear clothes that they normally wear while going out.

8. Trend fitting and predictions

Figure 6 shows some of the results of our trend fitting and prediction. The blue curve shows the empirical trend we observe from the data after recognition. The red curve shows the fit and prediction over the next year from our method. Other colors show the baselines fit and/or predictions from linear fit (yellow), exponential smoothing (magenta) and auto-regression (cyan).

Images	City	Attribute	Event week	Top-5 words in caption
	Seattle	Dress	2014-44	halloween, freaknight, freaknight2014, happyhalloween, halloween2014
	Bogota	Yellow	2014-24	mundial, seleccin, colombia, eres, yo
	Bangkok	Multiple layers	2016-04	amado, nora, winter, cold, led-er
	Paris	Long sleeve	2014-28	haute couture, couture, haute, chanelcouture, parisfashion-week
	Moscow	No sleeve	2014-31, 2014-32	summer, redsquare, man, sea, starlite
	Moscow	Long sleeve	2014-26, 2015-29	bnw, summer, summertime, photojournalism, parklive
	Bangkok	Graphics	2014-16, 2015-16	songkran, festival, songkranfestival, wet, songkarn
	Kyiv	No sleeve	2015-24	olgalomaka, university, vcg, themindparasites, master
	Bangkok	Red	2014-05, 2015-08, 2016-06	chinese, year, valentine, happy, happychinesenewyear
	Bangkok	Outerwear	2016-04	winter, cold, nora, portrait, the-outerproject
	Moscow	No sleeve	2014-21, 2014-23	park, may, bazaar, summer, evening
	Moscow	Tank top	2014-30, 2014-31	summer, sunny, sun, me, you
	Chicago	Graphics	2015-25	cup, hn, stanley, stanley, dynasty
	Jakarta	Red	2014-05	cny, chinese, pinggul, lingkar, year
	Vancouver	Dress	2014-44	halloween, happyhalloween, costume, halloween2014, costumes
	Los Angeles	Long sleeve	2015-19, 2015-20, 2015-21	dragcon, uscgrad, classof2015, graduation, rupaulsdragcon
	Kyiv	Long sleeve	2014-26	master, konvorablyk, okeanelzy, graduation, citybeachclub
	Istanbul	Short sleeve	2015-39	bayram, bayramlar, purgatory-istanbul, avclar, iyibayramlar

Images	City	Attribute	Event week	Top-5 words in caption
	Los Angeles	Multiple layers	2015-20	uscgrad, dragcon, salvador, ecommerce, classof2015
	Buenos Aires	Short sleeve	2014-34	philips, thevamps, thesouth, ptywonderland, goprobrasill
	Buenos Aires	One layer	2014-43	toque, meias, livraria, sim, senortango
	Berlin	Outerwear	2015-31	dey, eps, sharing, became, they
	Paris	Wearing jacket	2014-28	haute couture, couture, australia, pela, parish haute couture
	Delhi	Outerwear	2014-51, 2014-52	christmas, merry, winter, winters, santa
	Moscow	Outerwear	2014-25, 2014-26	dryn the city, drydry, river, summer, um
	Bangkok	Purple	2015-14	bikini, you, milin, in, zaapon-sale
	Istanbul	T-shirt	2015-39	hdr, bayram, purgatory istanbul, bayramlar, avclar
	Buenos Aires	One layer	2014-34	thevamps, buenos aires strip, philips, gopro brasill, selfie go-pro
	Moscow	Tank top	2014-32	russian, we, vscomoscow, skateboarding, skateboard
	Paris	Multiple layers	2014-28, 2015-31	haute couture, couture, mini, july, pfw
	Delhi	Wearing jacket	2014-51, 2014-52	christmas, merry, winter, winters, santa
	Buenos Aires	Not wearing jacket	2014-43	meias, livraria, toque, sim, senortango
	Moscow	One layer	2014-21, 2014-23	linkin park, bosco fresh fest, bw, park, may
	Moscow	Tank top	2014-21, 2014-23	instasize, park, evening, hall, like
	London	Wearing hat	2013-52	christmas, merry, xmas, jag, att
	Rome	Wearing scarf	2015-01	capodanno, year, cold, new, last

Images	City	Attribute	Event week	Top-5 words in caption
	Toronto	Not wearing jacket	2015-19	cmw2015, mothers, tcaf, mothersday, mother
	Buenos Aires	Wearing glasses	2015-02	formulae, frias, monument, out, of
	Bangkok	Blue	2015-33	bikeformom, mother, mom, bike, queen
	Seattle	Graphics	2014-05, 2015-05	superbowl, sb49, bluefriday, bowl, gohawks
	Seoul	Wearing scarf	2013-38	glamjourneys, glam, breakfast, awesomazingtrips, awesomazingkorea
	London	No sleeve	2014-30, 2015-27	picnic, park, hyde, seaside, wimbledon
	Seattle	Wearing hat	2014-06	parade, celebrate48, seahawks, 12thman, champions
	Buenos Aires	Wearing glasses	2015-01	virada, goprohero3, maravilhoso, foi, worldclub
	Delhi	Multiple layers	2014-51, 2014-52	christmas, merry, winters, santa, winter
	Toronto	One layer	2015-19	cmw2015, mothers, tcaf, mothersday, mother
	Los Angeles	Wearing jacket	2015-20	uscgrad, dragcon, salvador, ecommerce, delta
	Berlin	Wearing jacket	2014-34, 2015-31	hercules, interrail, august, reunited, bln2014
	Rome	Short sleeve	2014-41, 2014-42	granfondo, statigram, instahub, breakfast, jj
	Istanbul	Wearing hat	2013-50, 2015-01, 2015-02	kar, snow, siyah, instapic, winter
	Berlin	Not wearing jacket	2014-21	brumfitt, berlinbiennale, goat, exam, swan
	Berlin	Long sleeve	2014-34, 2015-31	hercules, bln2014, dey, aug, interrail
	Moscow	Not wearing jacket	2014-21, 2014-23	linkinpark, boscofreshfest, bw, park, may
	London	One layer	2015-27	wireless, wimbledon, wireless-festival, independenceday, iftar

Images	City	Attribute	Event week	Top-5 words in caption
	Berlin	Multiple layers	2014-34, 2015-31	hercules, interrail, august, schultheiss, beutel
	Tokyo	No sleeve	2014-44	halloween, happyhalloween, halloween2014, missinternational2014, cooljapan
	Berlin	One layer	2014-21	brumfitt, berlinbiennale, goat, exam, swan
	Vancouver	Tank top	2014-34	seawheeze, vansweaty, half, marathon, seawheeze2014
	Buenos Aires	Not wearing jacket	2014-34	thevamps, buenosairestrip, philips, goprobrasill, selfiego-pro
	Osaka	Not wearing jacket	2015-18, 2015-19	gw, aktr, goldenweek, electrox, bicycle
	Kyiv	Suit	2014-09	yanukovich, die, rochas, moscow, lecture
	Austin	Wearing glasses	2013-40, 2013-41, 2014-40, 2015-41	acl, aclfest, austincitylimits, acl2013, aclfestival
	Buenos Aires	Wearing glasses	2015-03	patos, ferias, verano2015, mavtips, picoftheday
	Moscow	Black	2014-26	june, xtcnyj, wu, wagner, uboat
	Austin	Wearing scarf	2013-48	thanksgiving, thankful, game, sisters, me
	Moscow	Wearing scarf	2014-01, 2015-02	fun, winter, instalike, tagsforlikes, yo
	Singapore	Suit	2015-21	npgraduation2015, graduation, poly, years, graduated
	Rio	Plaid	2015-26	ficacomigo, festajunina, eva, niver, fica
	Istanbul	One layer	2015-39	bayram, bayramlar, purgatory-istanbul, iyibayramlar, avclar
	Toronto	Short sleeve	2015-19	tcac, mothersday, mother, mothers, sportinglife10k
	Toronto	Dress	2014-44	halloween, happyhalloween, costume, halloween2014, costumes
	Berlin	Wearing jacket	2015-25, 2015-26	coffeeme, rosabaya, derblumigfruchtige, nespresso, arpeggio








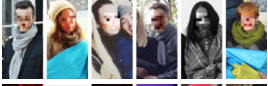

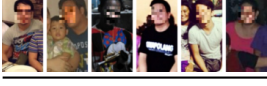
Images	City	Attribute	Event week	Top-5 words in caption
	Tokyo	Outerwear	2015-01	year, il, happynewyear, alla, newyear
	Beijing	Graphics	2015-35	beijing2015, t9, com, na, de
	Berlin	Wearing scarf	2015-01	year, snow, neve, new, berlim
	Moscow	Solid	2014-26	parklive, topmodelbygaga-worldmodels, podwallbar, modelsschool, tfp
	Bangkok	Red	2015-52	christmas, merry, mas, sleeve, merrychristmas
	Paris	Outerwear	2014-28, 2015-31	haute couture, couture, pela, july, created
	Tokyo	Dress	2014-44	halloween, happyhalloween, missinternational2014, tricko-rtreat, halloween2014
	Kyiv	Wearing scarf	2015-42	autumn, spain, bracken, foot-ball, it
	Milan	Dress	2015-09	mfw, fw15, milanfashionweek, mfw15, fashionweek
	Manila	T-shirt	2014-01	newyear, happynewyear, eve, newyear2014, pesos





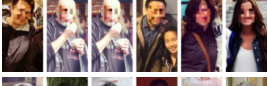

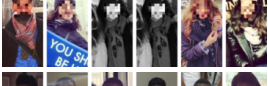
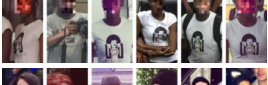







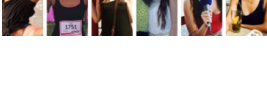
Table 6: Top 100 events detected across the world by finding anomalous behaviour in attribute trends. The words from captions are sorted by their TF-IDF scores in the event week. Images from each event are sorted by the number of words matching with the top-5 keywords

Images	City	Event week	Top-5 words in caption
	Bangkok	2014-49, 2015-49, 2015-50	dad, father, bike, bikefordad, day
	Rio	2014-24, 2014-25, 2014-26, 2014-27, 2014-28	worldcup, copa, brasil, copadomundo, torcida
	Sao Paulo	2014-24, 2014-25, 2014-26, 2014-27	worldcup, vaibrasil, copa, brasil, worldcup2014
	Austin	2013-40, 2013-41, 2014-40, 2014-41, 2015-41	acl, aclfest, aclfestival, austincitylimits, music
	Madrid	2015-14	alcal, demadridalcielo, puerta, than, more
	Moscow	2014-01, 2015-01, 2015-02, 2016-01	winter, newyear, new, christmas, year
	Istanbul	2015-39	bayramlar, fotoraf, falan, avclar, voodoo
	Jakarta	2014-05	chinese, year, xi, gong, cny
	Vancouver	2015-52	christmas, merry, holidays, merrychristmas, jardinsdeparis
	Austin	2015-37	game, longhorns, hookem, football, hook
	Rome	2013-48	thanksgiving, xtreme, think, temple, sorryjoeforcuttingoffyourface
	Austin	2015-12, 2016-11	sxsw, sxsw2016, sxsw2015, live, ran
	Austin	2014-11	sxsw, sxsw2014, sxsw14, band, music
	Madrid	2014-03	sido, seorita, rush, pornoortografa, nikilauda
	Seattle	2015-11	lucky2015, dash, st, rave, luckysea
	Kolkata	2013-41	parikrama, puja, durgapuja, durga, festival
	Moscow	2014-01, 2015-02, 2016-01	newyear, winter, gum, redsquare, rink
	Bangkok	2014-21	scott, set, man, woman, freesize

Images	City	Event week	Top-5 words in caption
	Sao Paulo	2015-04, 2016-06	carnaval, favorvel, tranquilo, good, dessa
	Kyiv	2014-09	yanukovich, kiev, ukraine
	Moscow	2014-26	walk, super, day, girls, with
	Budapest	2015-01	beautiful, side, river, winter, newyear
	Paris	2015-27	way, vogue, lovely, july, from
	Nairobi	2015-30	ges2015kenya, obama, potus, ges2015, president
	Tokyo	2016-12	graduation, photo, thank, university, rikkyo
	Jakarta	2014-40	batik, national, day, nasional, kenyang
	Moscow	2014-23	woman, vsco, like, followme, beautiful
	Kolkata	2014-17	statue, shiva, parvati, mantra, lordganesha
	Paris	2014-28	haute couture, good, modeling, aftershow, gopro
	Tokyo	2015-32	vol, instapic, ykykwedding, travelgram, tourist
	Istanbul	2015-02	standing, sevgiler, geceler, eyp, corner
	Kyiv	2015-21	happy, girls, with, white, relax
	Rio	2015-26	ficacomigo, festajunina, eva, niver, sobre
	Austin	2014-50, 2015-50	christmas, formal, party, tx, been
	Seattle	2014-44	halloween, freaknight, freaknight2014, happyhalloween, halloweek
	Seattle	2014-06, 2015-04	celebrate48, parade, seahawks, bowl, marinersff

Images	City	Event week	Top-5 words in caption
	Kolkata	2013-34	seriouslook, randomclick, rakhi, jatt, instafame
	Jakarta	2014-25	electro, electrorun, run, glow, set
	Sao Paulo	2015-37	municipal, face, ministro, direito, vamos
	Bogota	2013-44	halloween, modelo, blue, red, kids
	Seattle	2013-45	pic, morning, place, tour, big
	Bangkok	2015-04	l34, b40, dd, gray, smile
	Seoul	2016-12	seoulfashionweek, 2016fw, sfw, ddp, fashion
	Istanbul	2016-15	gece, biz, senden, imdi, btn
	Chicago	2015-25	cup, stanleycup, stanley, parade, champions
	Budapest	2015-14	spring, today, midnight, some, walk
	Berlin	2015-23	uclfinal, league, juventus, juvefcb, go
	Seattle	2015-50	holiday, party, guys, them, these
	Rome	2014-15	rodjendan, gf, day2, by, glam
	Kyiv	2014-36	where, travel, this, so, city
	Osaka	2014-44	halloween, loofah, colorful, ariel, amemura
	Tokyo	2015-01	year, new, day, sale, happiness
	Nairobi	2014-14	house, after, live, the
	Bangkok	2015-08	chinese, year, b2, new, dragon

Images	City	Event week	Top-5 words in caption
	Sydney	2014-45	melbournecup, melbourne, cup, race, races
	Moscow	2014-21, 2014-23	may, happy, friends, star, park
	Paris	2015-49	cop21, climate, at, change, of
	Bangkok	2015-37	samarnmitr58, here, tpcback2school, asia, are
	Sydney	2014-39	listen, surry, sleepout, sash, nightlife
	Austin	2013-48	thanksgiving, thankful, longhorns, football, turkey
	Kyiv	2013-50	euromaidan, euromajdan, winter, my, europe
	Paris	2014-38	da, oh, ver, tudo, maison
	Lagos	2013-52	christmas, merry, black, live, family
	Rome	2013-47	hold, between, re, amore, europe
	Bogota	2013-36	colombia, toda, familia, vamos, ganar
	Rio	2015-01	ano, happynewyear, vem2015, reveillon, primeiro
	Jakarta	2014-30	best, god, back, team, surprise
	Sydney	2014-36	vfno, father, spring, around, vogue
	Budapest	2015-14, 2016-12	budapest, una, of, travel, picoftheday
	Berlin	2015-01	berlin, germany, crazy, gopro, eurotrip
	Singapore	2014-47, 2014-48, 2015-47	prom, ever, picture, best, part
	Berlin	2015-33	us, welcome, summer2015, mauerpark, berlinerdom

Images	City	Event week	Top-5 words in caption
	Tokyo	2015-21	not, fashion, t2shibuya, t2, every
	Kyiv	2013-37	in, girls, friends, ukraine, kiev
	Cairo	2015-18	omarkhairat, we, concert, study, jesuitien
	Kyiv	2013-39, 2013-40	instagood, tagsforlikes, black, style, me
	Vancouver	2016-09	canada, prime, minister, globe2016, his
	Seattle	2013-39	shrimps, outta, moose, amazonuw, school
	Bangkok	2015-36	congratulations, school, be, to, by
	Paris	2013-48	beauty, louloute, have, only, notredamede-paris
	Lagos	2014-46	d2d, inspiration, motivation, livethedream, lenovo
	Paris	2013-52	vacations, christmas, louvre, nice, good
	Istanbul	2014-46	10kasm, mustafakemalatatrck, atam, anyoruz, burcuerdemwedding
	Kolkata	2013-36	sweet, bullride, bull, for, my
	Istanbul	2015-16	nn, fresh, use, selfiestick, havamis
	Moscow	2013-38, 2014-41	autumn, theatre, instasize, smile, instagood
	Seattle	2015-19	fancy, celebrating, starwars, spuspring, gas-works
	Austin	2015-12	sxsw, sxsw2015, showcase, like, dope
	Istanbul	2015-01	year, all, turchia, awesome, var
	London	2015-27	wireless, instafollow, drake, missed, pre











Images	City	Event week	Top-5 words in caption
	Kolkata	2013-48	wid, week, tonight, signature, reunion
	Rio	2015-53	ano, feliz2016, venha, copacabana, vem2016
	Rome	2014-42	how, sonia, holaitalia, giro, gialle
	Bangkok	2013-51, 2013-52	merry, christmas, mas, year, frank
	Kolkata	2015-01	nye, new, year, happynewyear, years
	Bogota	2014-49	night, eres, grado, no, mas
	Seattle	2015-02	gohawks, 12s, starbucks, first, seahawks
	Sydney	2014-02	boys, harbourbridge, fashion, love, walk
	Vancouver	2013-49	didn, december, outfit, ladies, afternoon
	Kolkata	2013-35	insta, earth, center, budhgaya, at

Table 7: Top 100 events detected across the world by finding anomalous behaviour in style trends. The words from captions are sorted by their TF-IDF scores in the event week. Images from each event are sorted by the distance from the style cluster center



Figure 2: Major events discovered by our framework in North and South American cities. For each event the figure shows the clothes that people wear for the events, the city, one of the months of occurrence and the most descriptive word extracted using the captions of images.

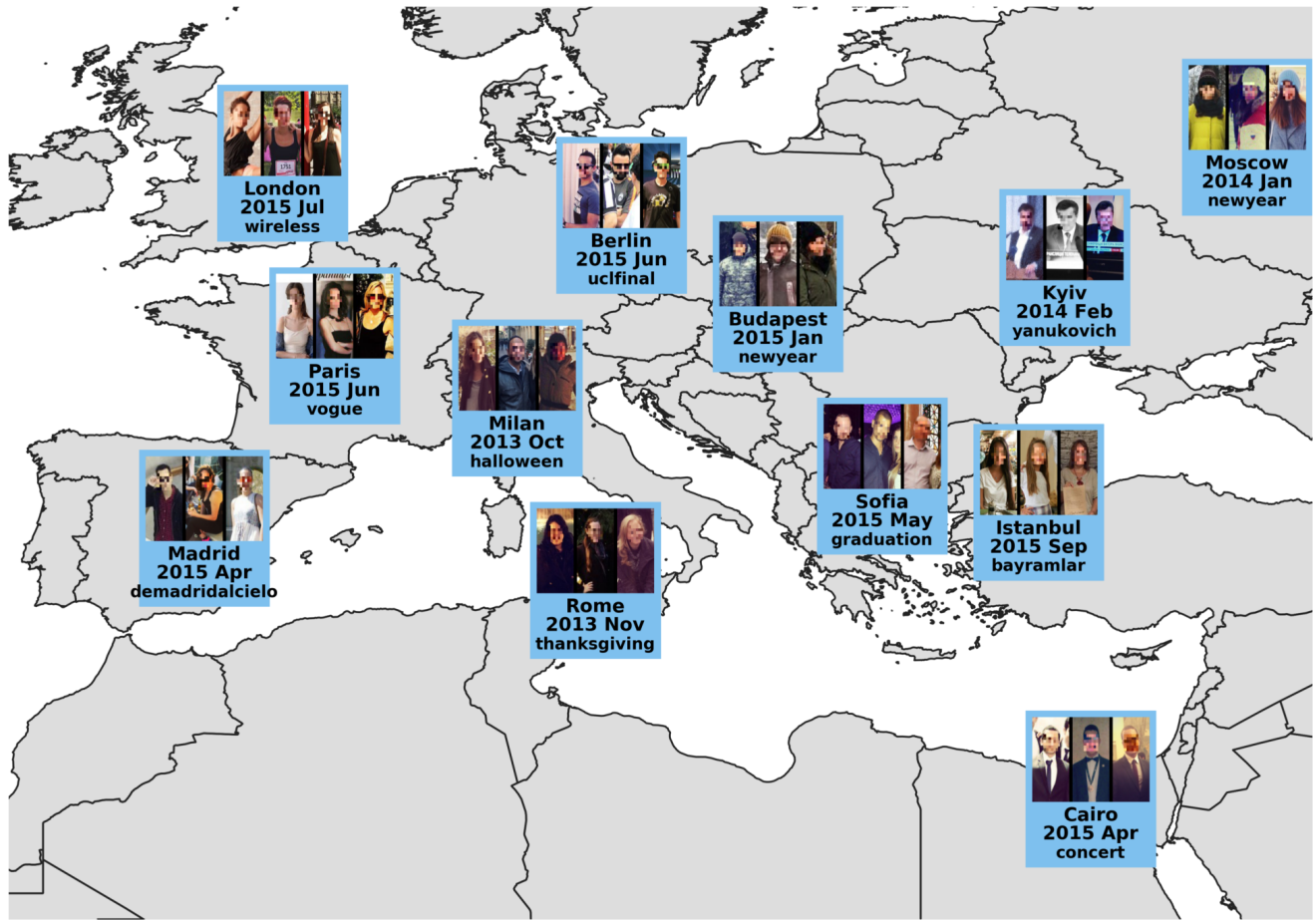


Figure 3: Major events discovered by our framework in European and North African cities (Events for rest of the African cities are shown in Figure 1 (Main paper)). For each event the figure shows the clothes that people wear for the events, the city, one of the months of occurrence and the most descriptive word extracted using the captions of images.

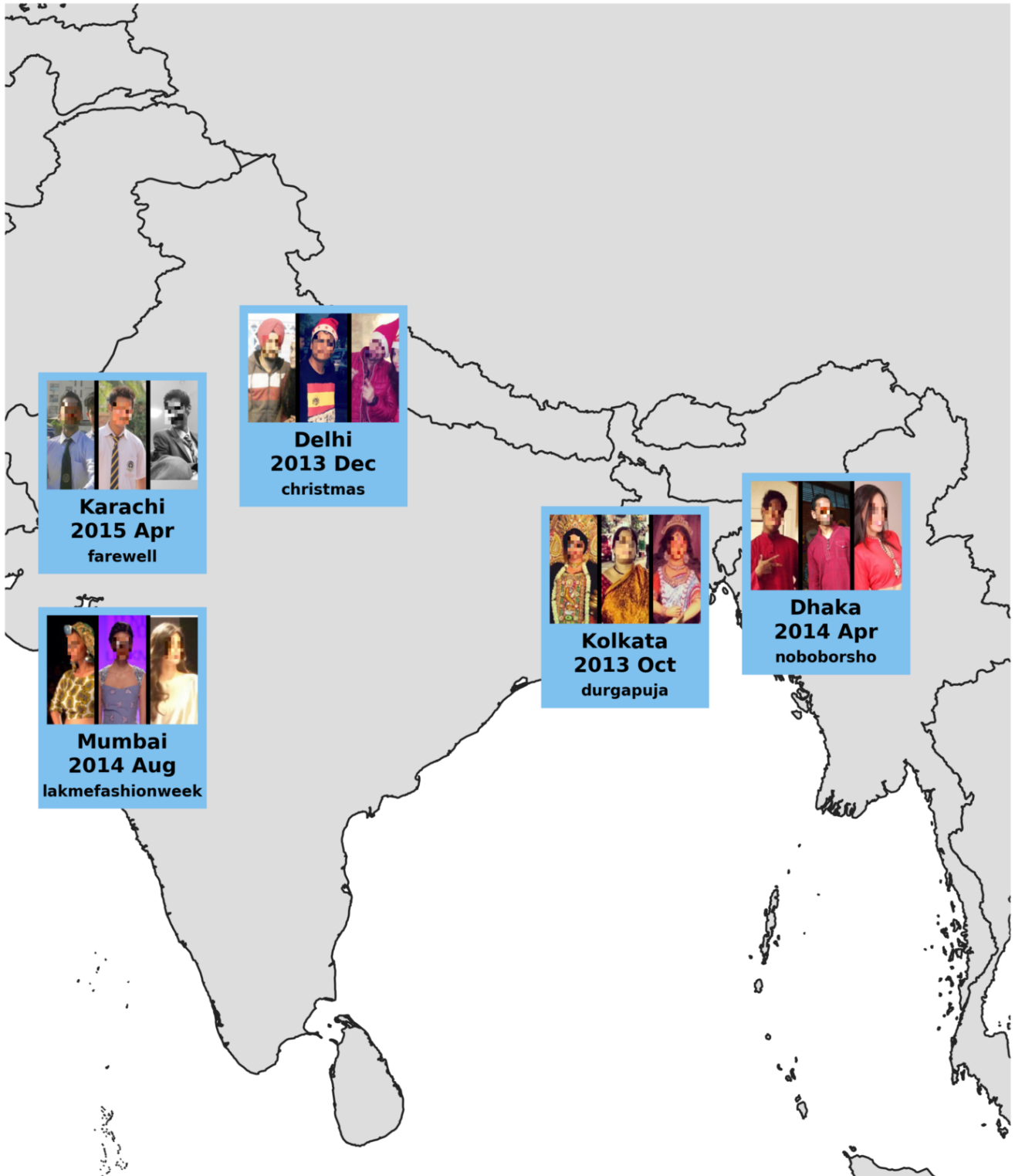


Figure 4: Major events discovered by our framework in South Asian cities. For each event the figure shows the clothes that people wear for the events, the city, one of the months of occurrence and the most descriptive word extracted using the captions of images.

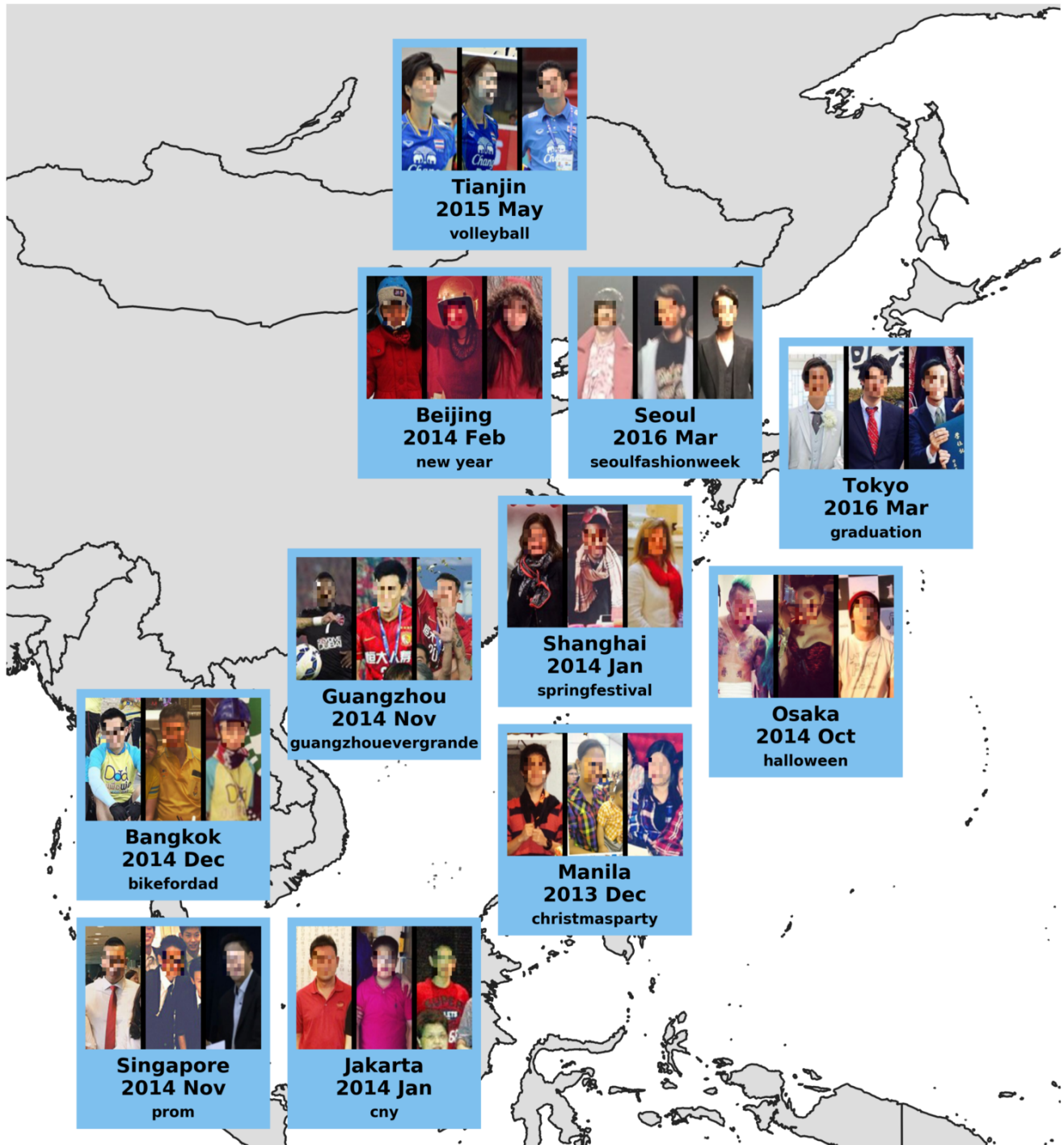


Figure 5: Major events discovered by our framework in South-East Asian cities. For each event the figure shows the clothes that people wear for the events, the city, one of the months of occurrence and the most descriptive word extracted using the captions of images.

References

- [1] Wikipedia contributors. Lunisolar Calendar. 1

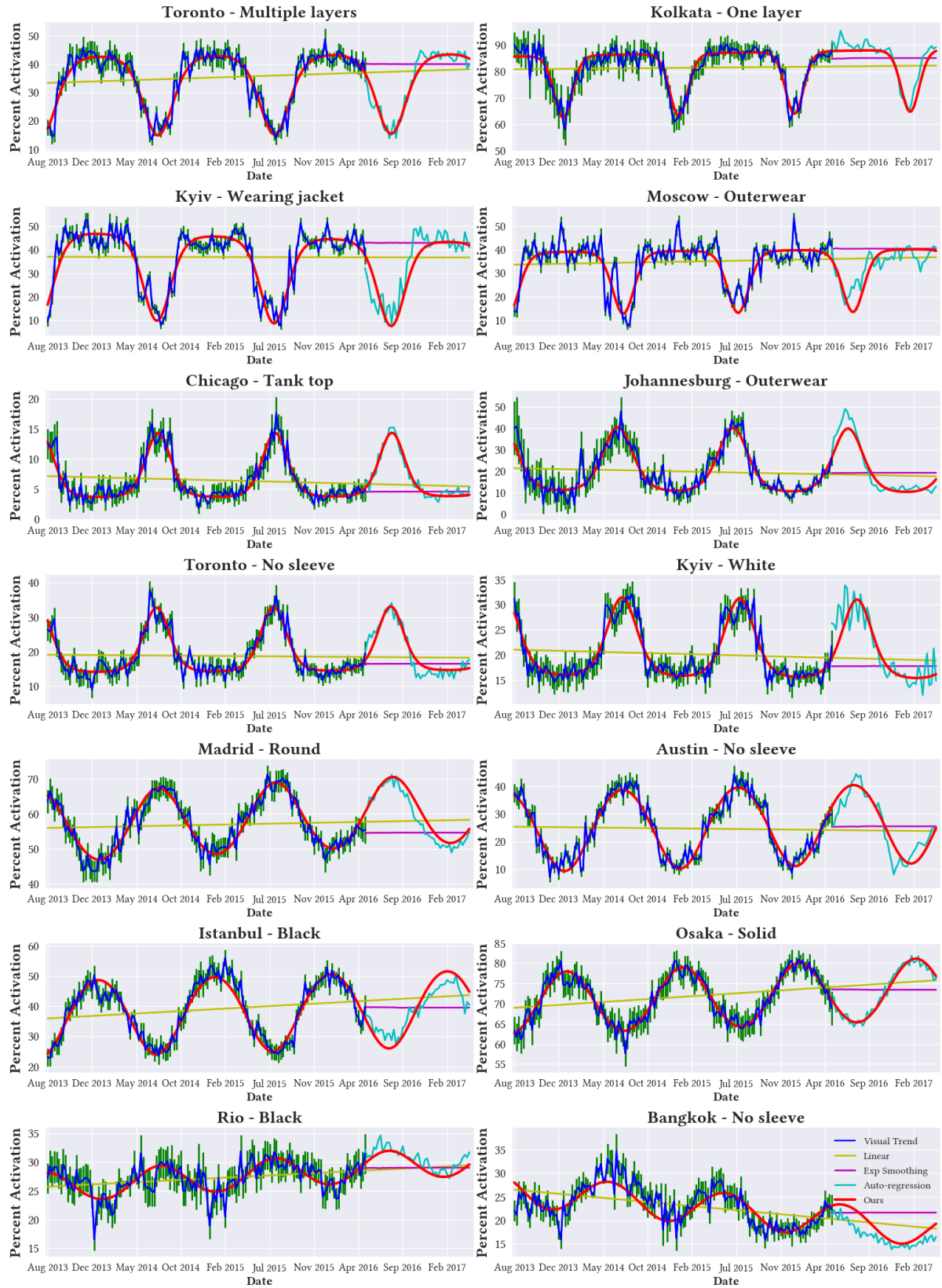


Figure 6: Some of the trends in different cities with our curve fits (Red). The top two rows show the trends with spikes downwards, the next two rows show trends with spikes upwards. The last three rows show trends following a sinusoidal pattern.