Mining Reaction and Diffusion Dynamics in Social Activities

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Online User Activity on the Web as Sensor

Post / Search

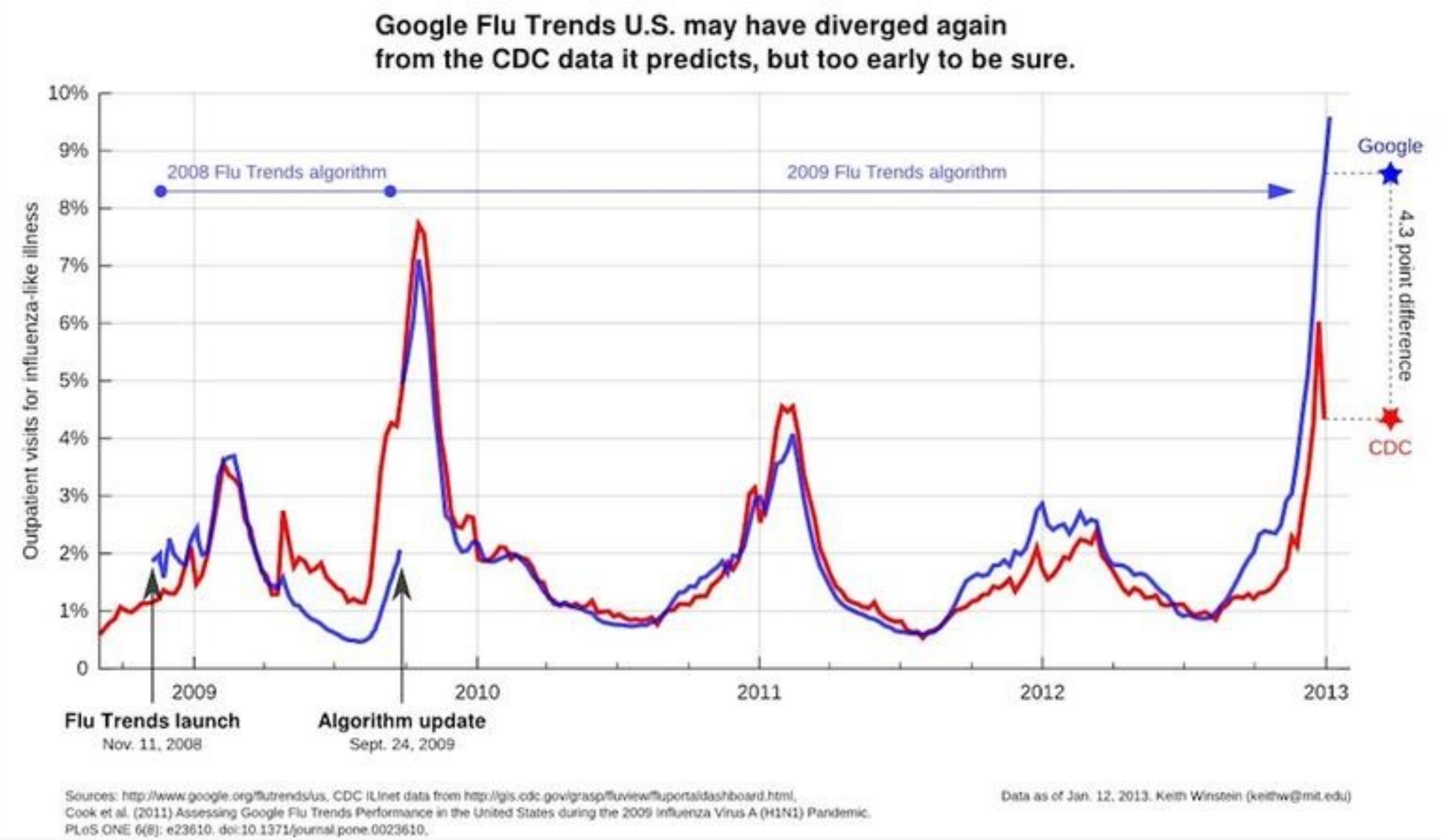
Recommendation
Feedback

Social sensor

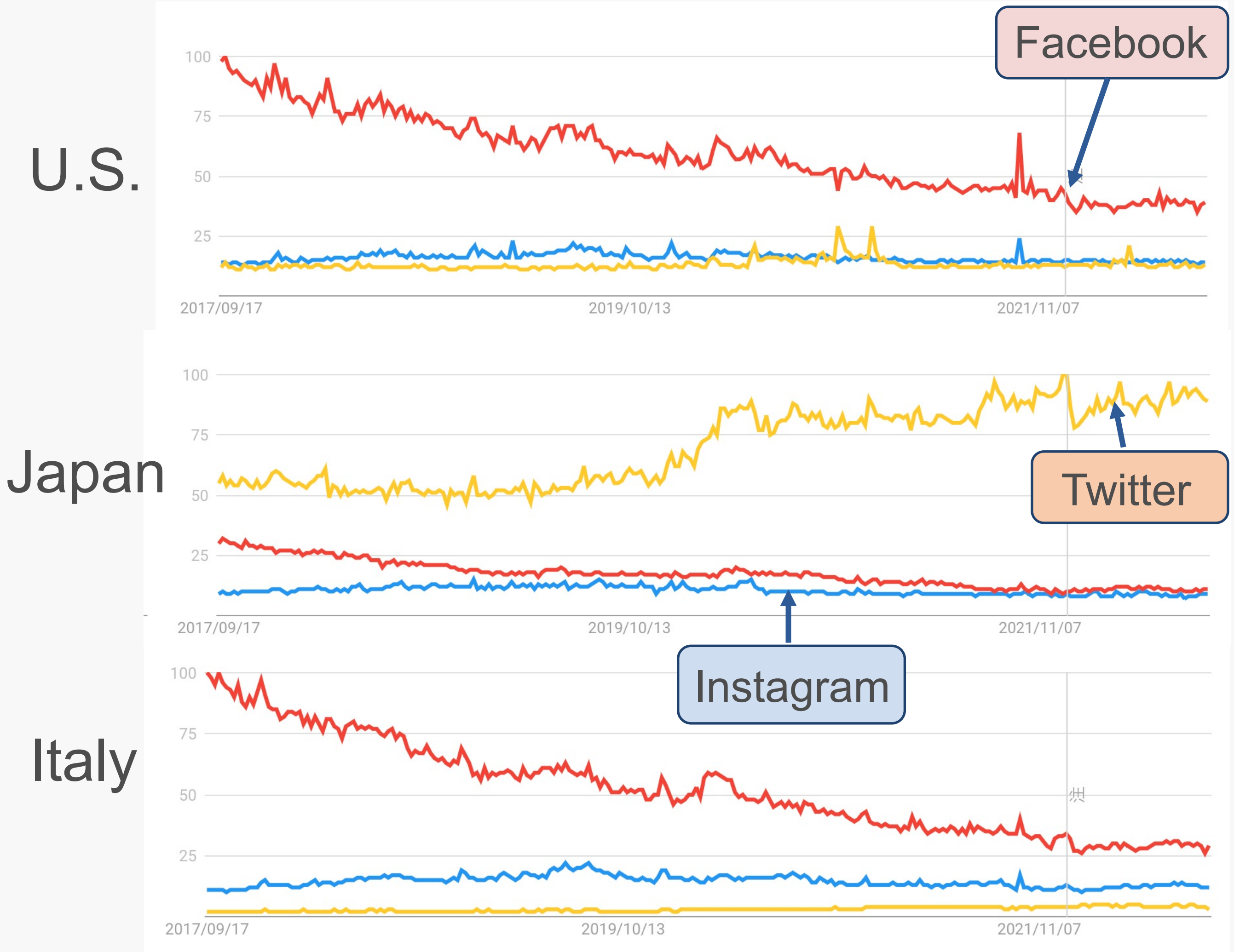
Physics World

Example: Google Flu

A system that predicts the number of influenza cases based on the volume of search queries based on linear regression



Search queries capture human interests



What's relations between items?

Facebook

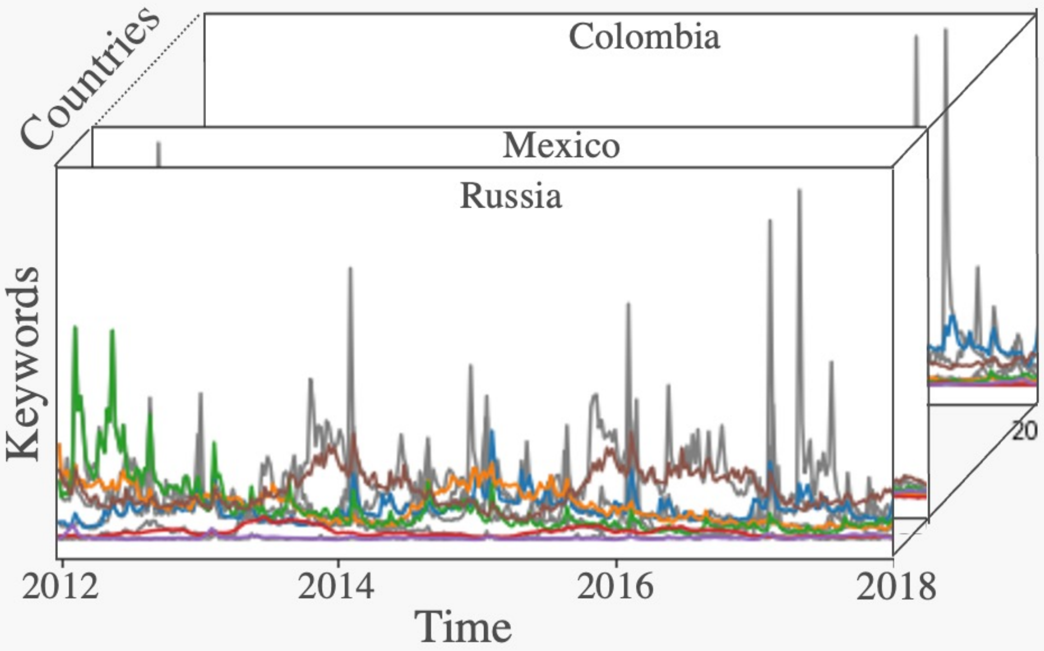
?

Twitter Instagram

What's interactions between countries?

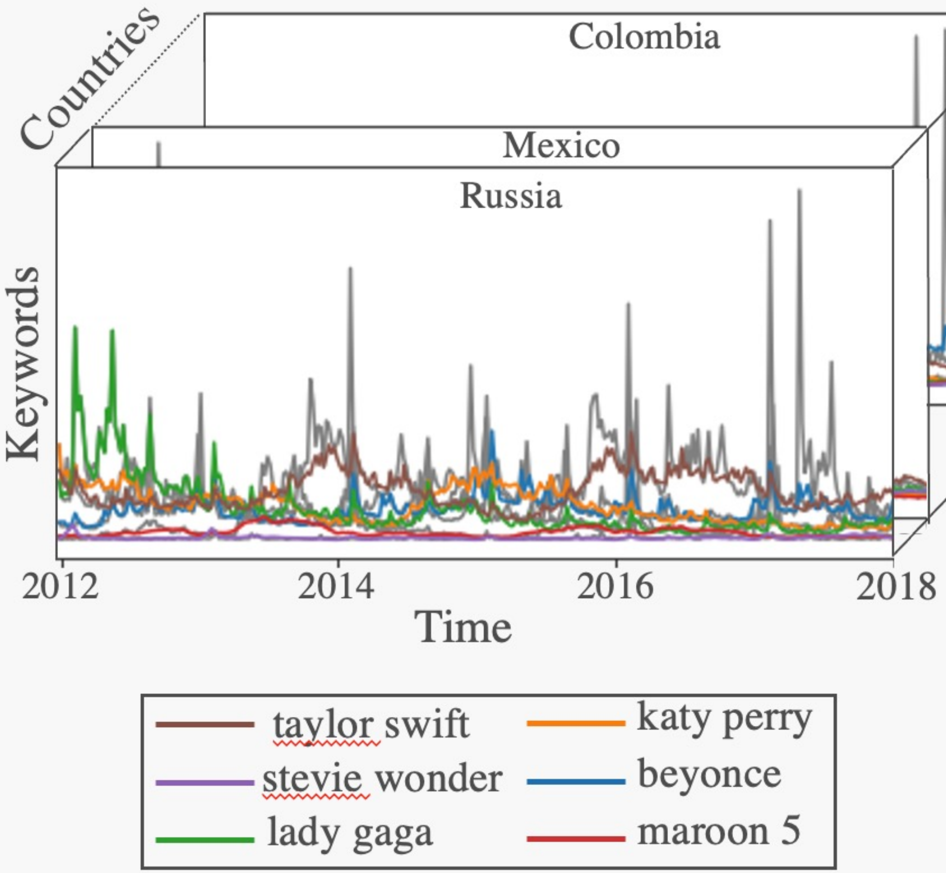
Given: online user activities

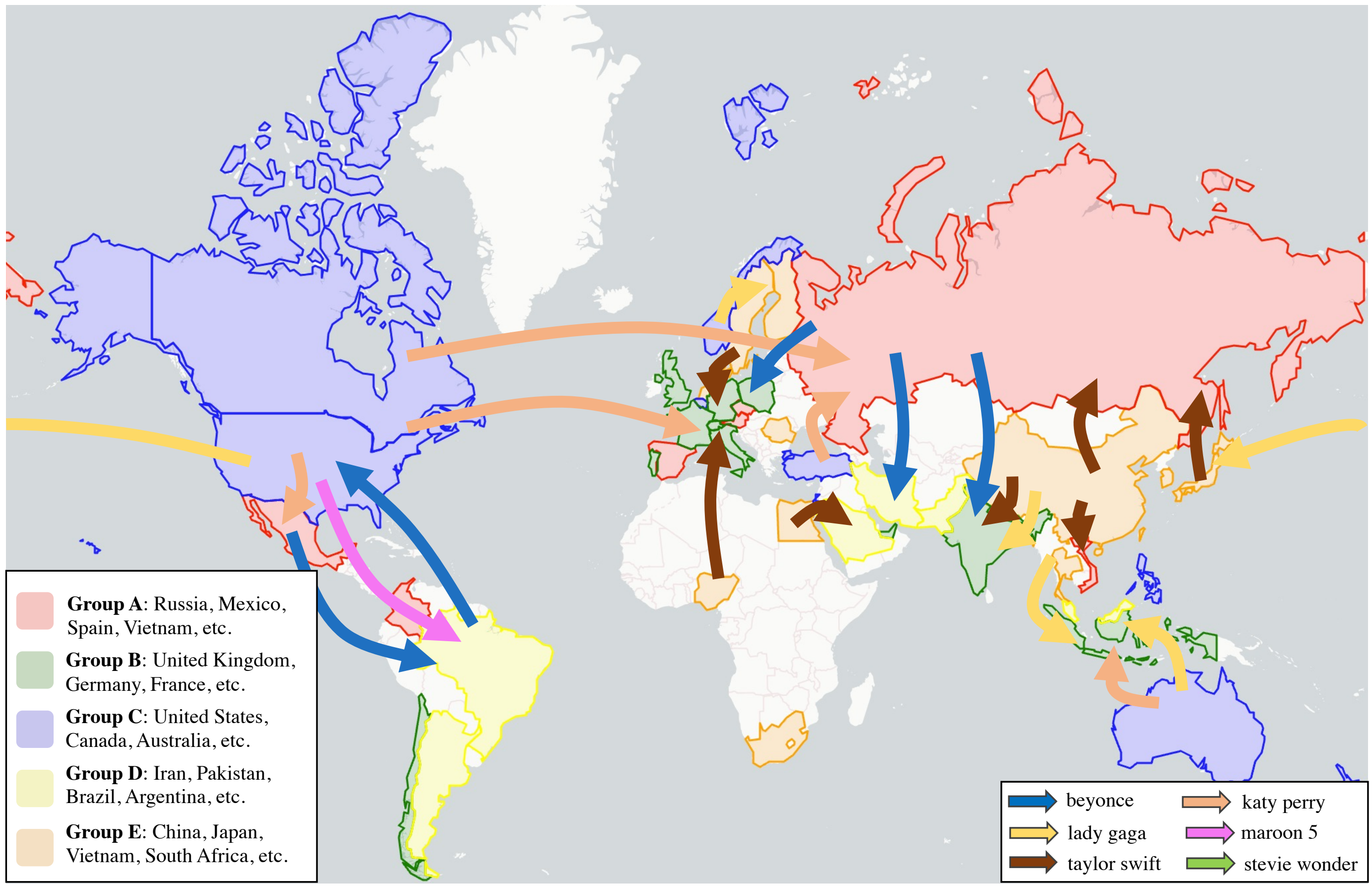
e.g., google search volumes



Goal 1: Diffusion flow of each group

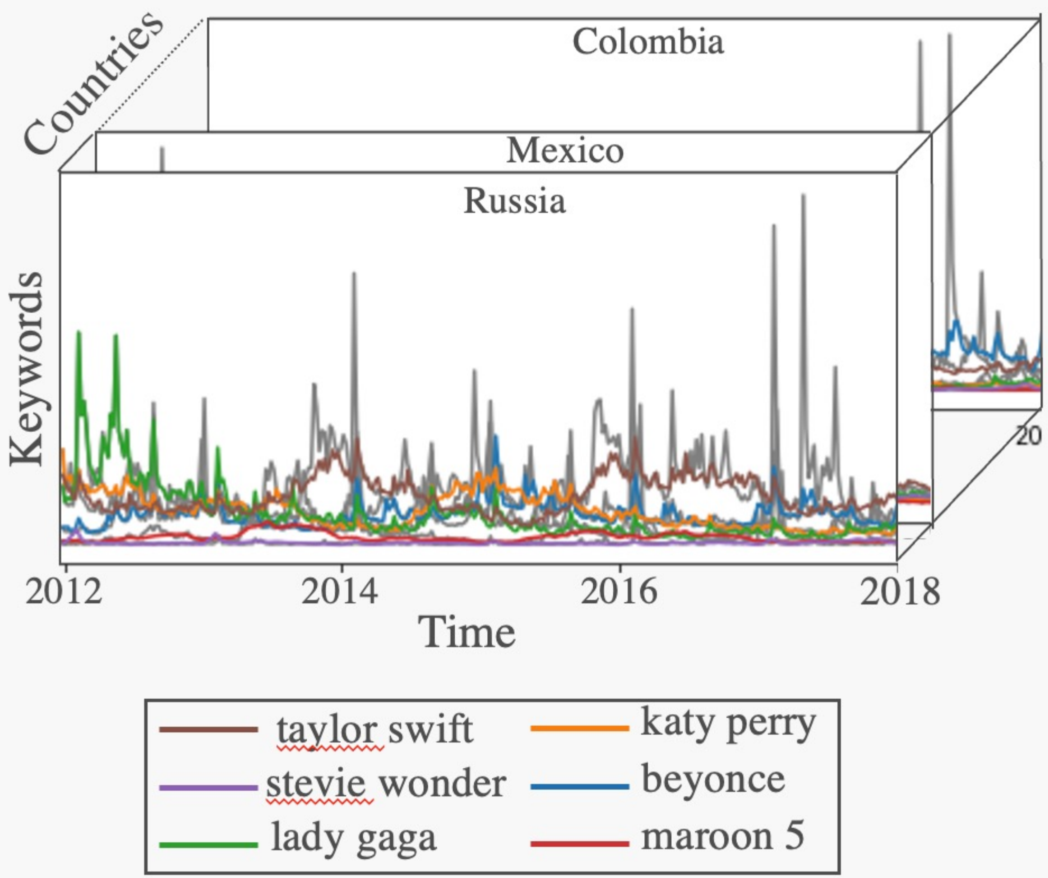
e.g., google search volumes

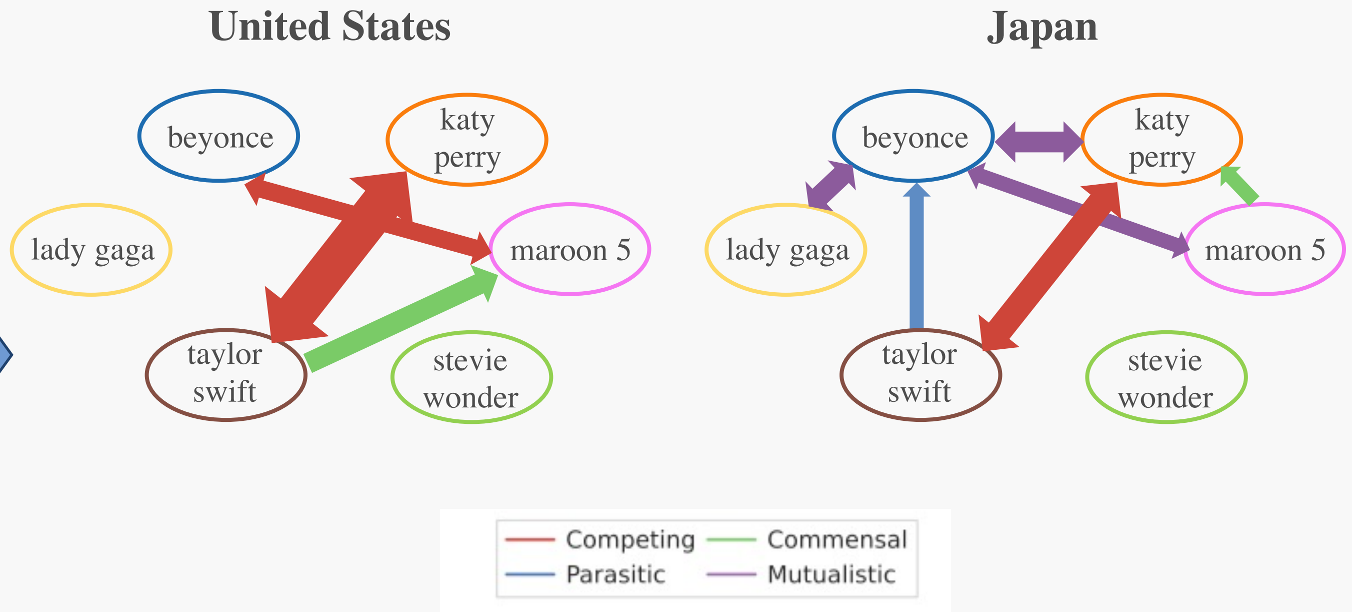




Goal 2: Interaction between keywords

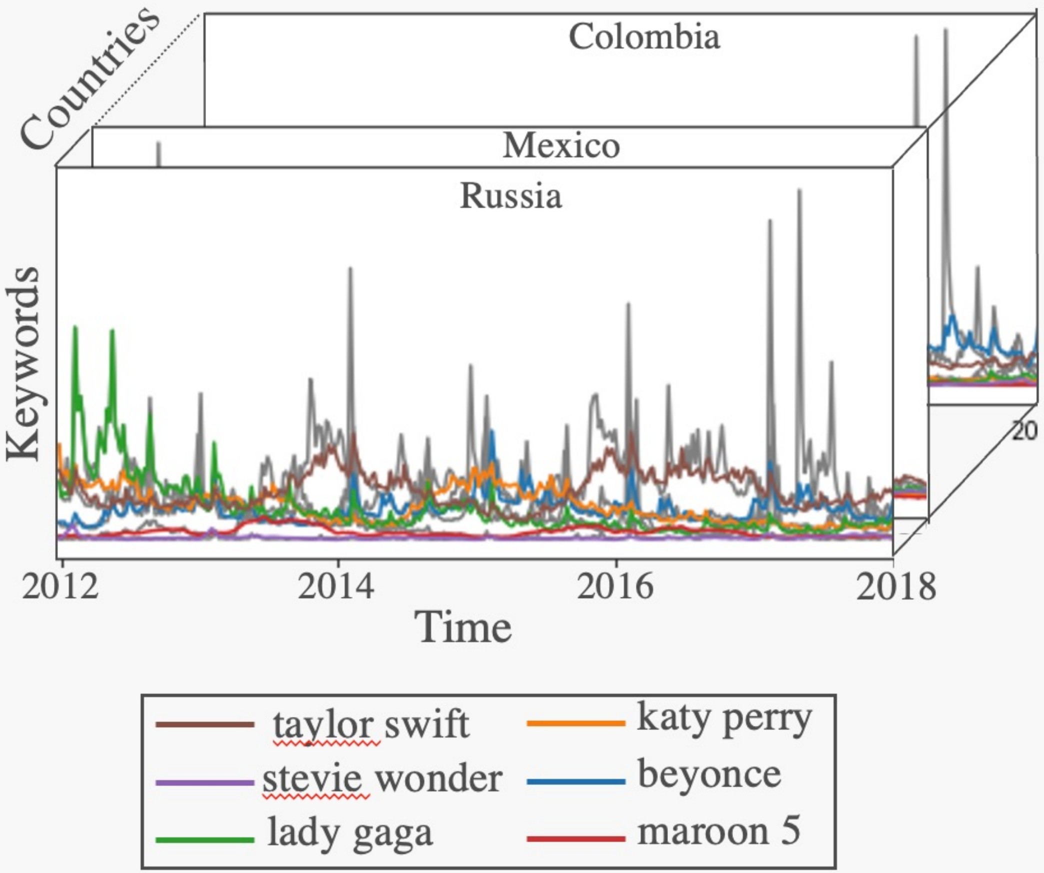
e.g., google search volumes

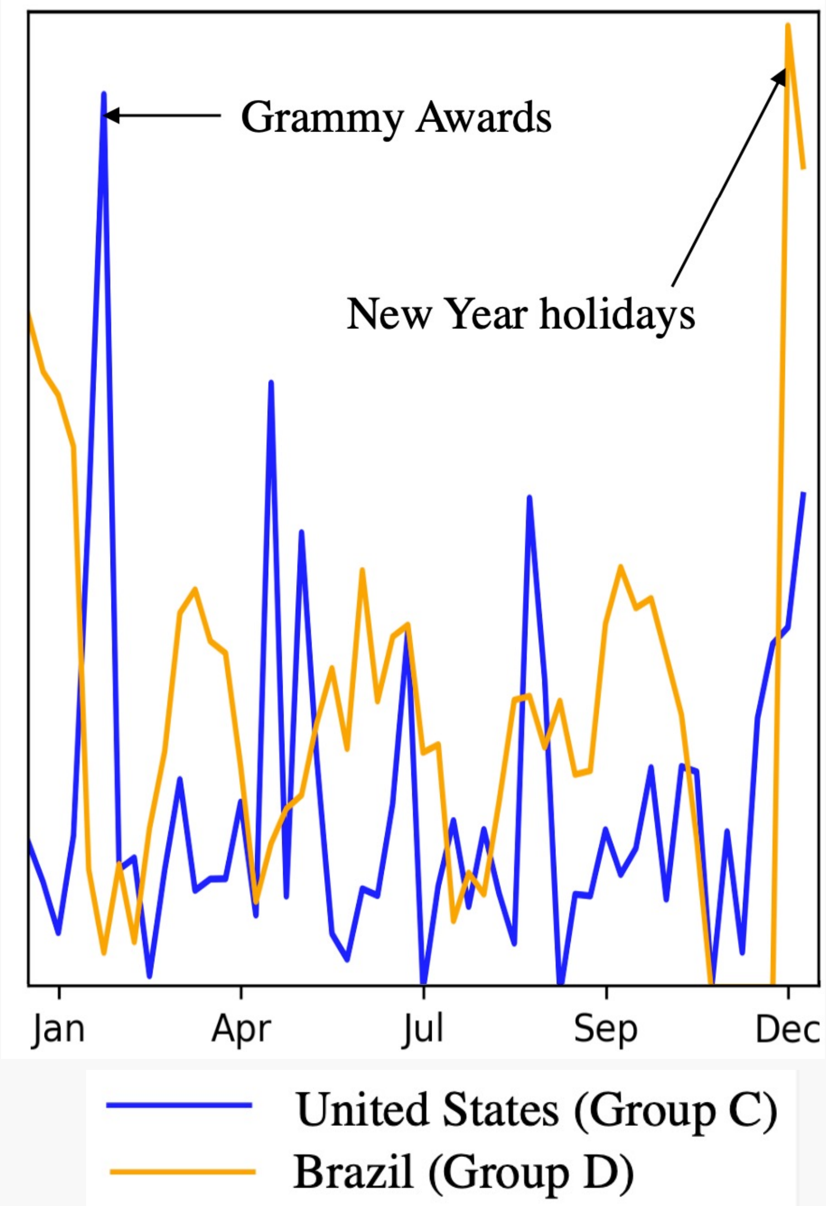




Goal 3: Seasonality

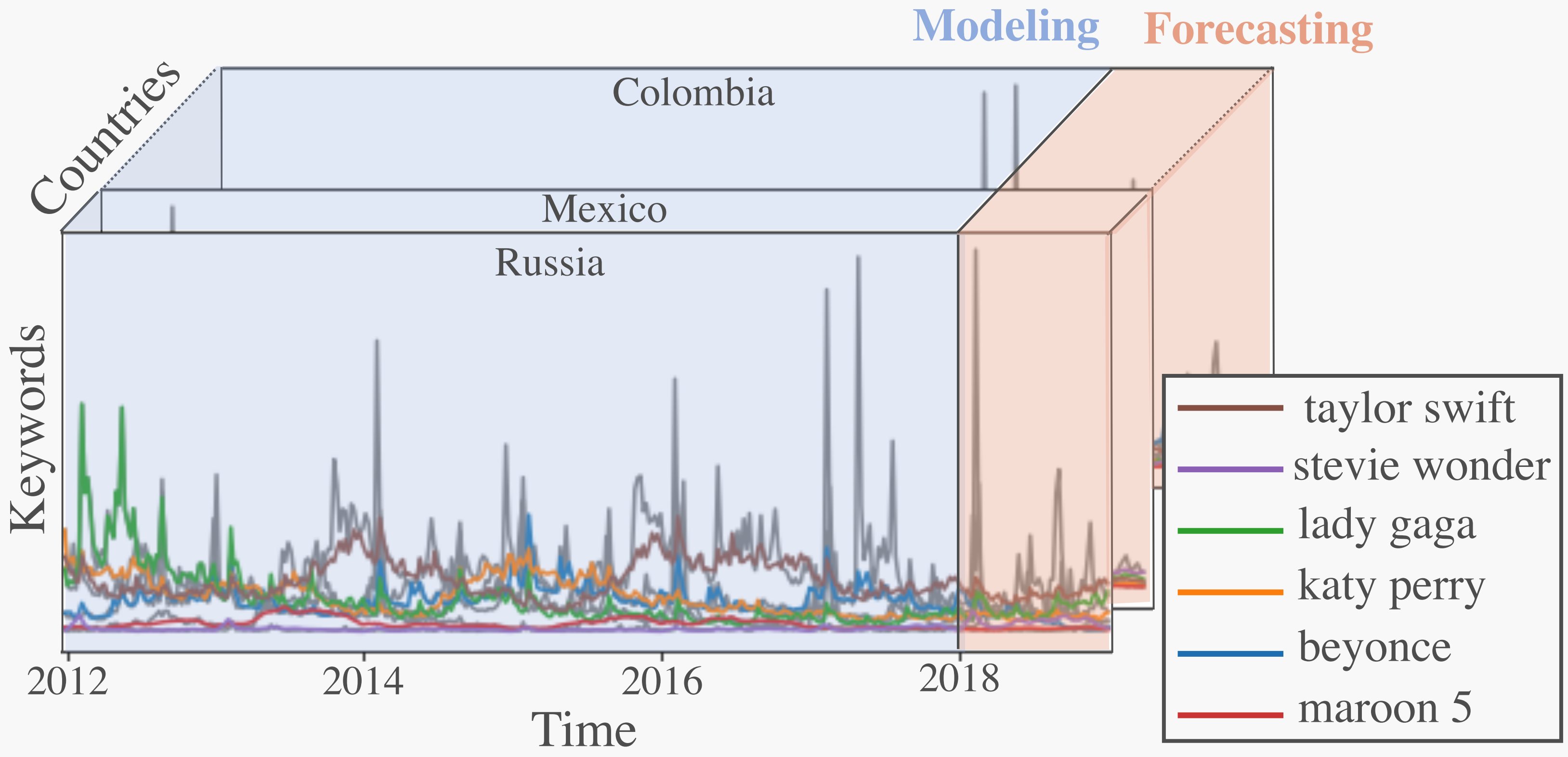
e.g., google search volumes





Goal 4: Good forecasting performance

e.g., google search volumes



Given: online user activities

Goal 1: Diffusion process of each group
Goal 2: Interaction between keywords
Goal 3: Seasonality
Goal 4: Good forecasting performance

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Goal 1: Diffusion process of each group
Goal 2: Interaction between keywords
Goal 3: Seasonality
Goal 4: Good forecasting performance

Our solution: FLUXCUBE
Reaction-diffusion system
+
Neural Network

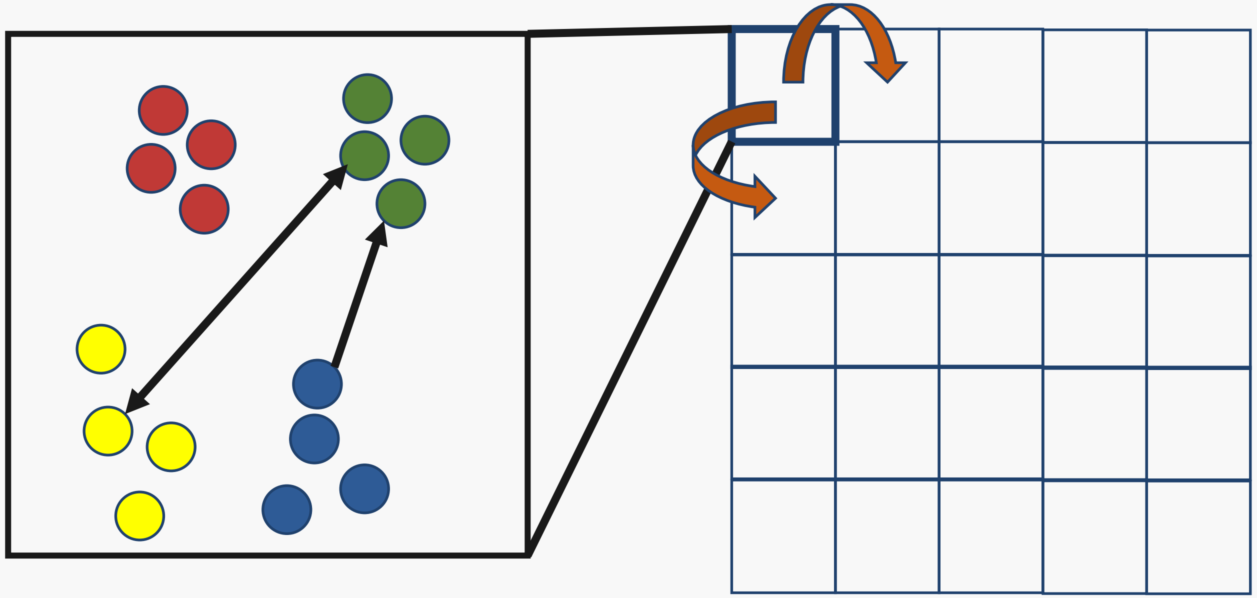
Application of Reaction-Diffusion System

Main Equation $$\frac{\partial \boldsymbol{u}}{\partial t} = \boxed{\boldsymbol{f}\left(\boldsymbol{u}, t\right)} + \boxed{\mathcal{D}\Delta u}$$

Reaction term

Diffusion term

Reaction-Diffusion System is utilized is a mathematical model corresponding for physical phenomena.



Application of Reaction-Diffusion System

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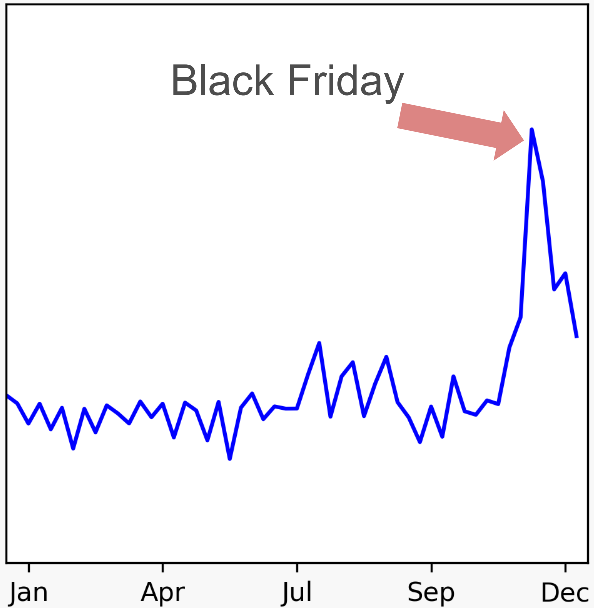
Seasonal term



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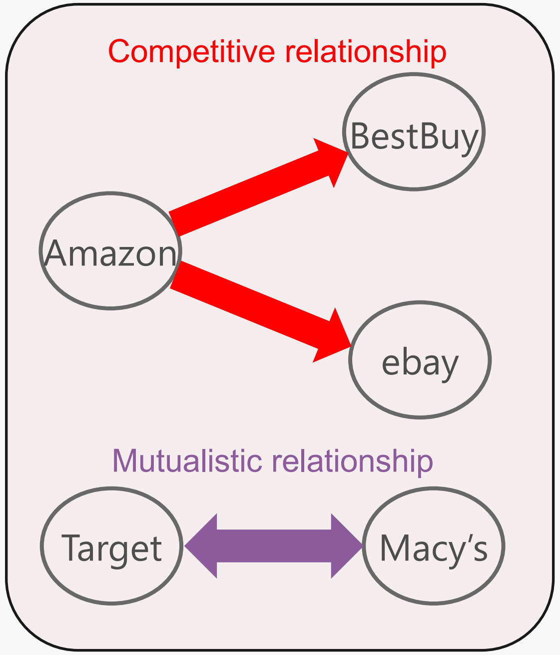
Reaction term



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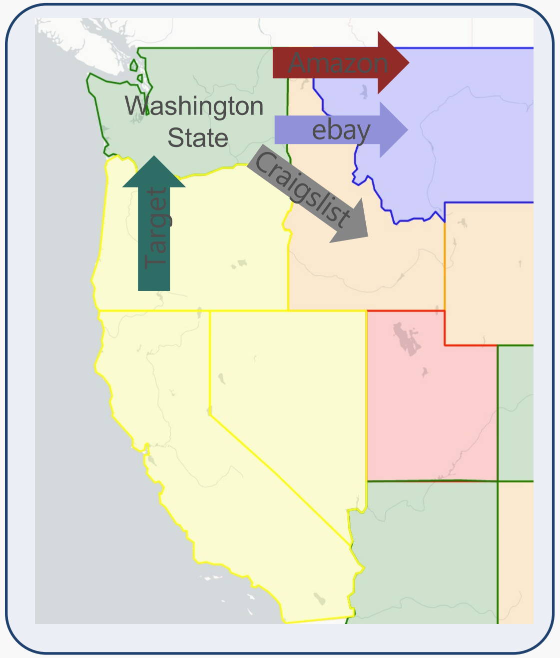
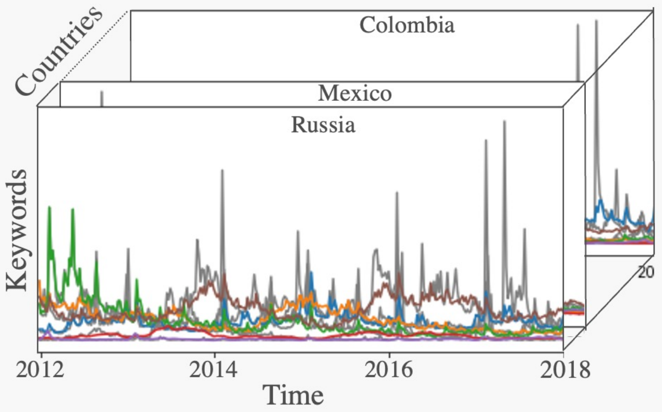
Diffusion term



Reaction-Diffusion $\frac{\partial \boldsymbol{u}}{\partial t} = \boxed{\boldsymbol{f}\ (\boldsymbol{u}, t)} + \boxed{\mathcal{D}\Delta u}$



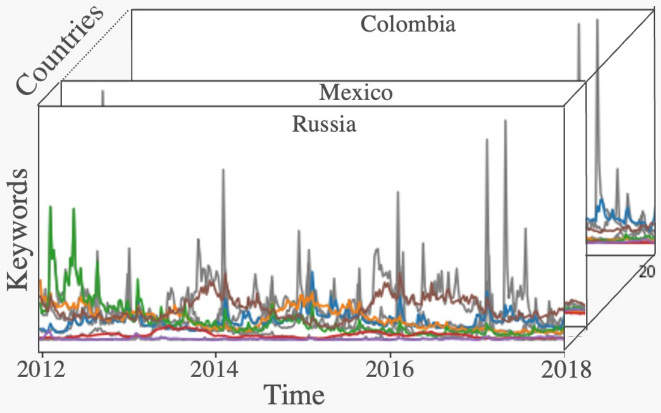
Input: $\chi = \{\boldsymbol{x_{tij}}\}$

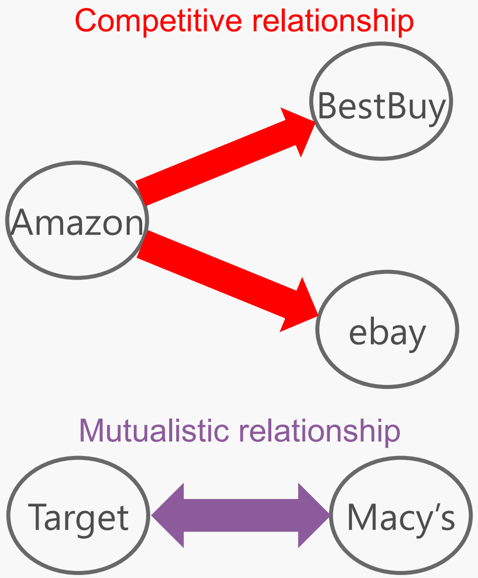
timestep t, location i, item j

FLUXCUBE

$$\frac{\partial x_{tij}}{\partial t} = \underbrace{\boxed{\boldsymbol{f}\left(x_{tij} | \boldsymbol{\chi_{t,i,:}}\right)}}_{\text{Reaction term}} + \underbrace{\boxed{\boldsymbol{g}\left(x_{tij} | \boldsymbol{\chi_{t}}, \boldsymbol{t}\right)}}_{\text{Diffusion term}}$$

$$\boxed{x_{t+1ij} = F\left(\frac{\partial x_{tij}}{\partial t} + x_{tij}\right)}$$





Reaction-Diffusion $\frac{\partial \boldsymbol{u}}{\partial t} = \boldsymbol{f}\left(\boldsymbol{u}, t\right) + \mathcal{D}\Delta u$

Reaction term

FLUXCUBE

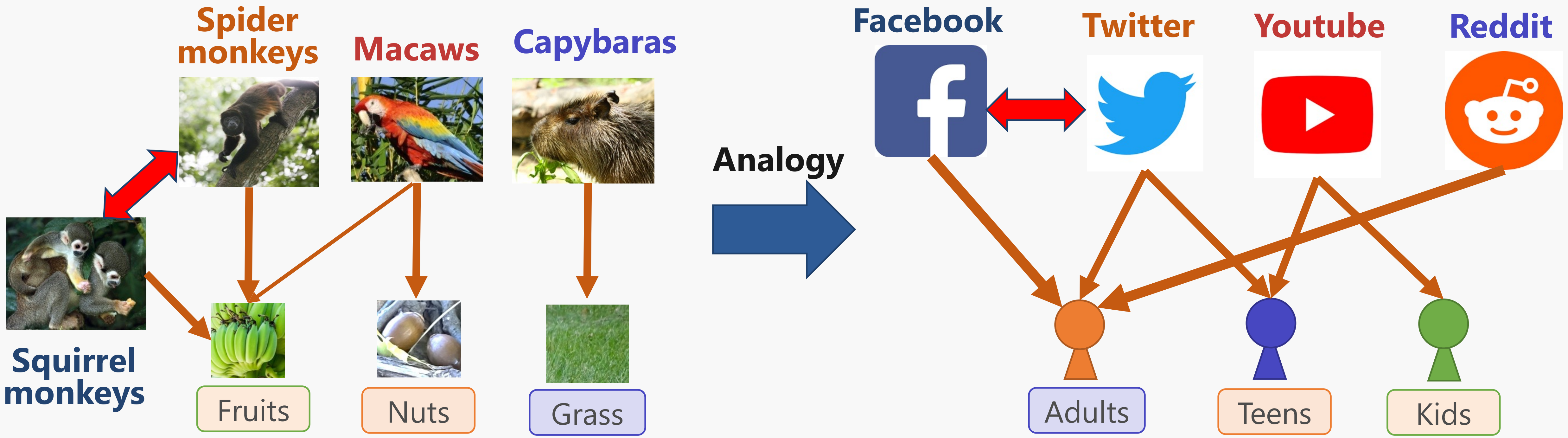
$$\frac{\partial x_{tij}}{\partial t} = \boxed{\boldsymbol{f}\left(x_{tij} | \chi_{t,i,:}\right)} + g\left(x_{tij} | \chi_t, \boldsymbol{t}\right)$$

Seasonal term

$$x_{t+1ij} = F\left(\frac{\partial x_{tij}}{\partial t} + x_{tij}\right)$$

Reaction term: component idea

Component idea: **Item interaction as Jungle**

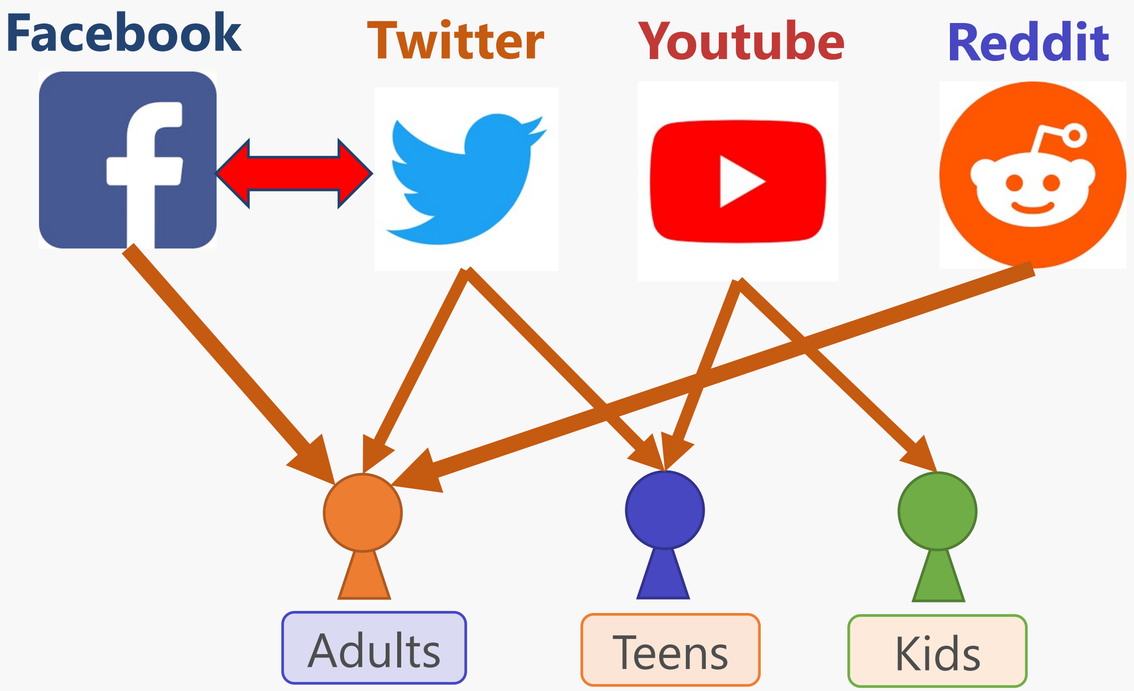


Reaction term: component idea

The idea represents as **Lotka-Volterra Equation**

$$a_j \chi_{t,i,j}\left(1 - \frac{\sum_{j'} c_{jj'} x_{tij'}}{b_j}\right)$$

- a_j: intrinsic growth rate of keyword j;
- b_j: carrying capacity of keyword j;
- $c_{jj'}$: intra/inter-keyword interaction strength from the j'-th keyword to the j-th keyword, which is each value in C



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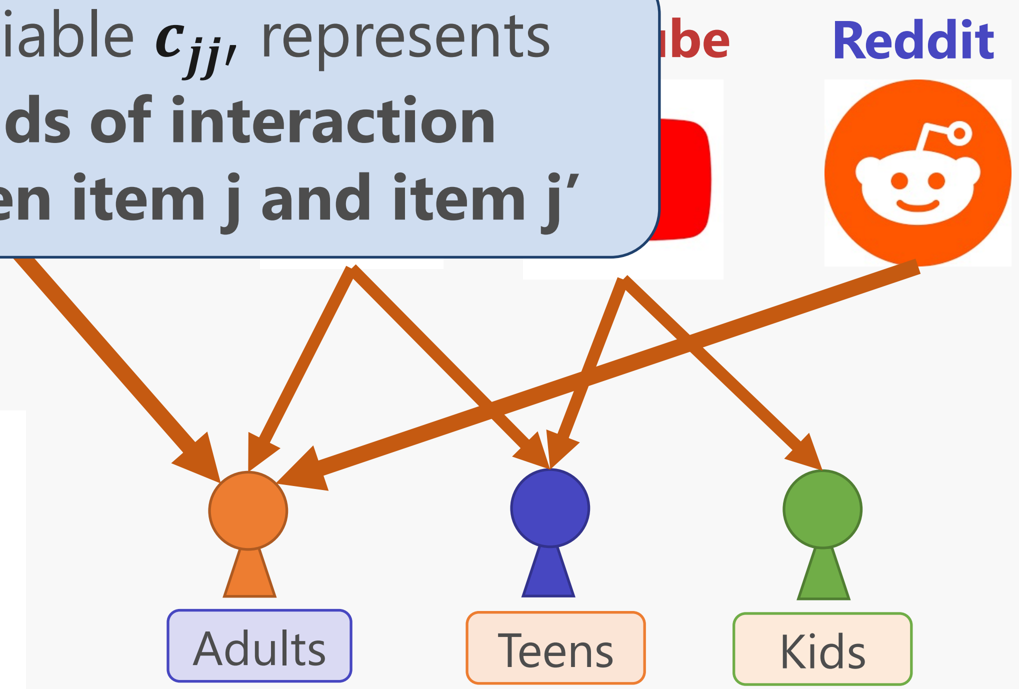
$$a_j \chi_{t,i,j} \left(1 - \frac{\sum_{j'} \boxed{c_{jj'}} x_{tij'}}{b_j} \right)$$

The variable $c_{jj'}$ represents **the kinds of interaction between item j and item j′**



- $c_{jj'} > 0, c_{j'j} > 0$: a competitive relationship
- $c_{jj'} < 0, c_{j'j} > 0$: a parasitic relationship
- $c_{jj'} < 0, c_{j'j} = 0$: a commensal relationship
- $c_{jj'} < 0, c_{j'j} < 0$: a mutualistic relationship

Reaction term: component idea

The idea represents as **Lotka-Volterra E**

$$a_j \chi_{t,i,j}\left(1 - \frac{\sum_{j'} \boxed{c_{jj'}}\, x_{tij'}}{b_j}\right)$$

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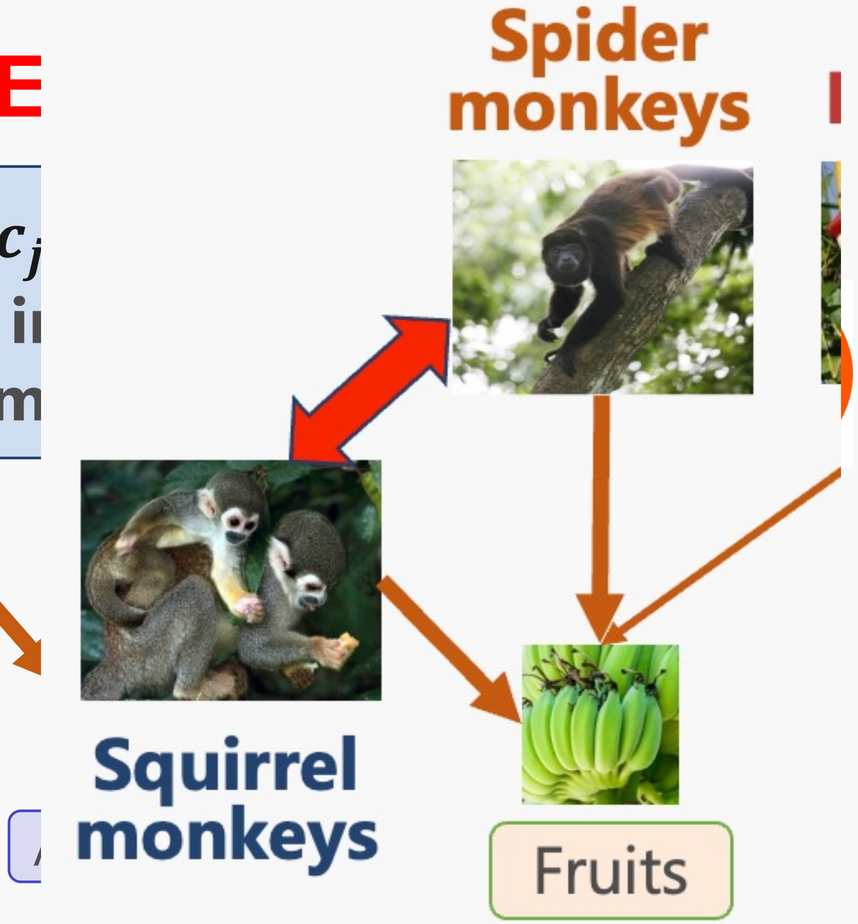

Reaction term: component idea

The idea represents as **Lotka-Volt**

$$a_j \chi_{t,i,j}\left(1-\frac{\sum_{j'} \boxed{c_{jj'}}\, x_{tij'}}{b_j}\right)$$

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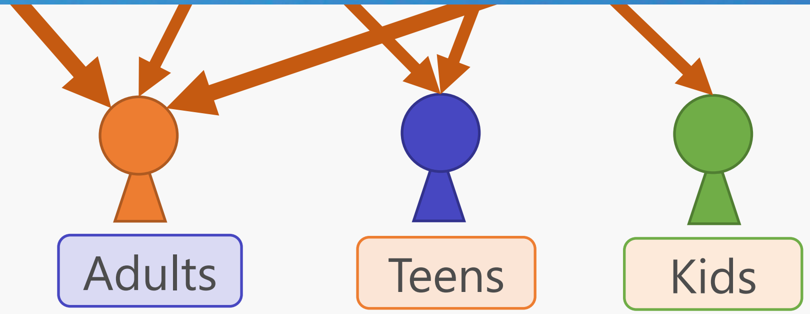

Reaction term: component idea

The idea represents as **Lotka-Volterra Equation**

$$a_j \boldsymbol{\chi}_{\boldsymbol{t},\boldsymbol{i},\boldsymbol{j}} \left(1 - \frac{\sum_{j'} \boxed{c_{jj'}}\, x_{tij'}}{b_j}\right)$$

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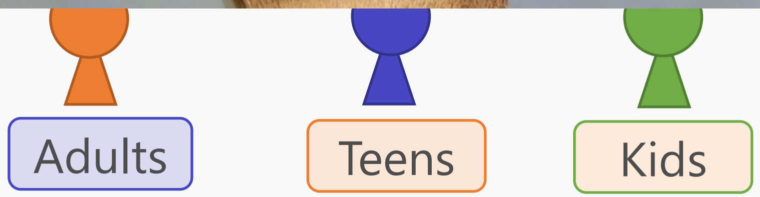

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The idea represents as **Lotka-Volterra Equation**

$$\textbf{FLUXCUBE:}\quad \frac{\partial x_{tij}}{\partial t} = \boxed{\boldsymbol{f}\left(x_{tij} \middle| \boldsymbol{\chi}_{\boldsymbol{t},\boldsymbol{i},:}\right)} + \mathcal{g}\left(x_{tij} \middle| \boldsymbol{\chi}_{\boldsymbol{t}}, \boldsymbol{t}\right)$$

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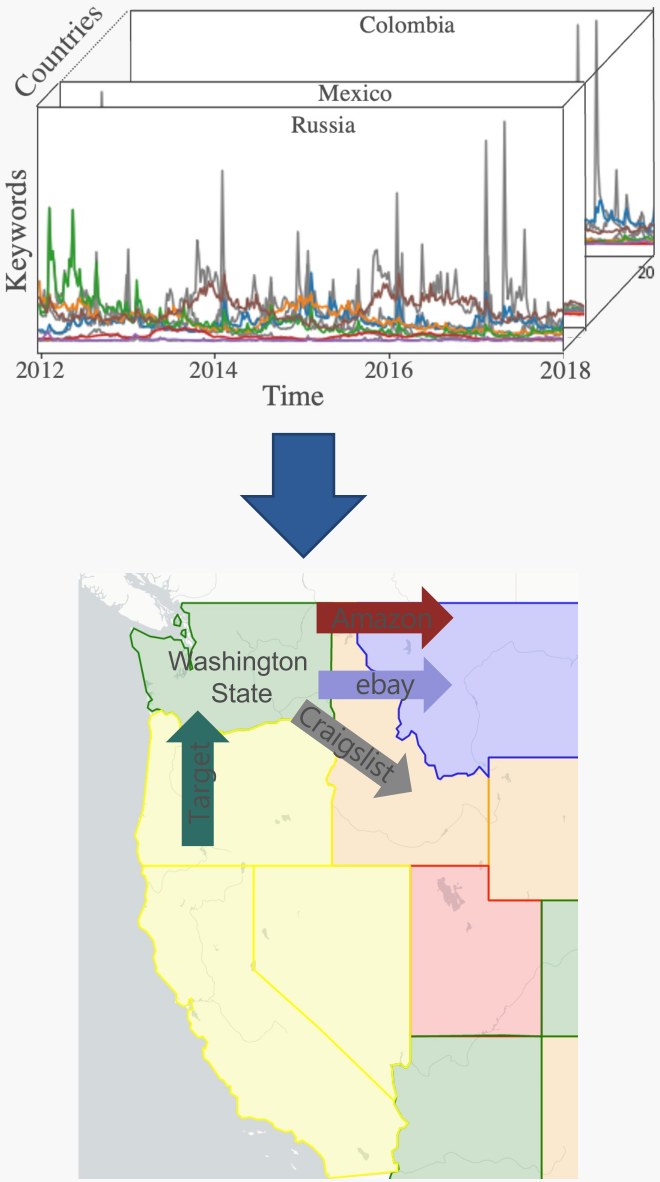

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Diffusion term

FLUXCUBE

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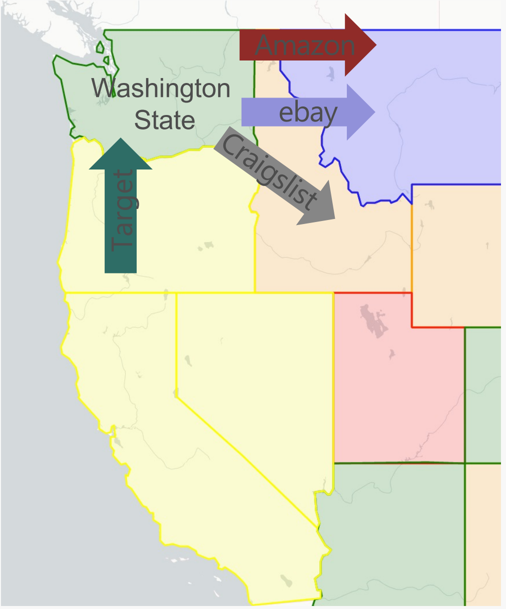
Seasonal term

$$x_{t+1ij} = F\left(\frac{\partial x_{tij}}{\partial t} + x_{tij}\right)$$

Reaction term: component idea

- The interactions of any keyword between locations are **not constant** because of external factors
- We need to **capture the time change of the interaction**, e.g., complex phenomena and rapid changes.



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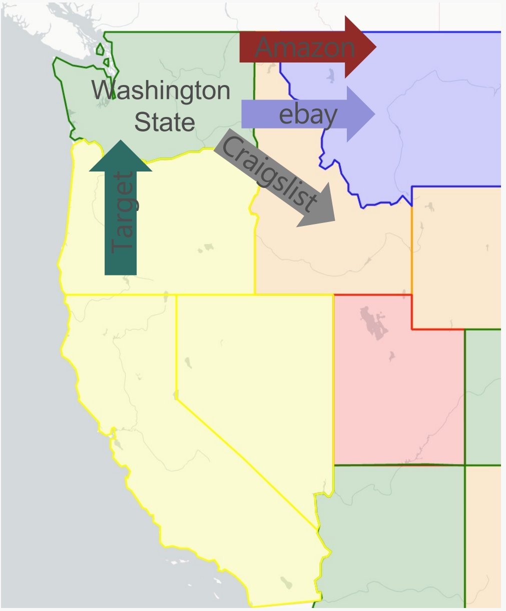


Our model represents the interaction by RNN

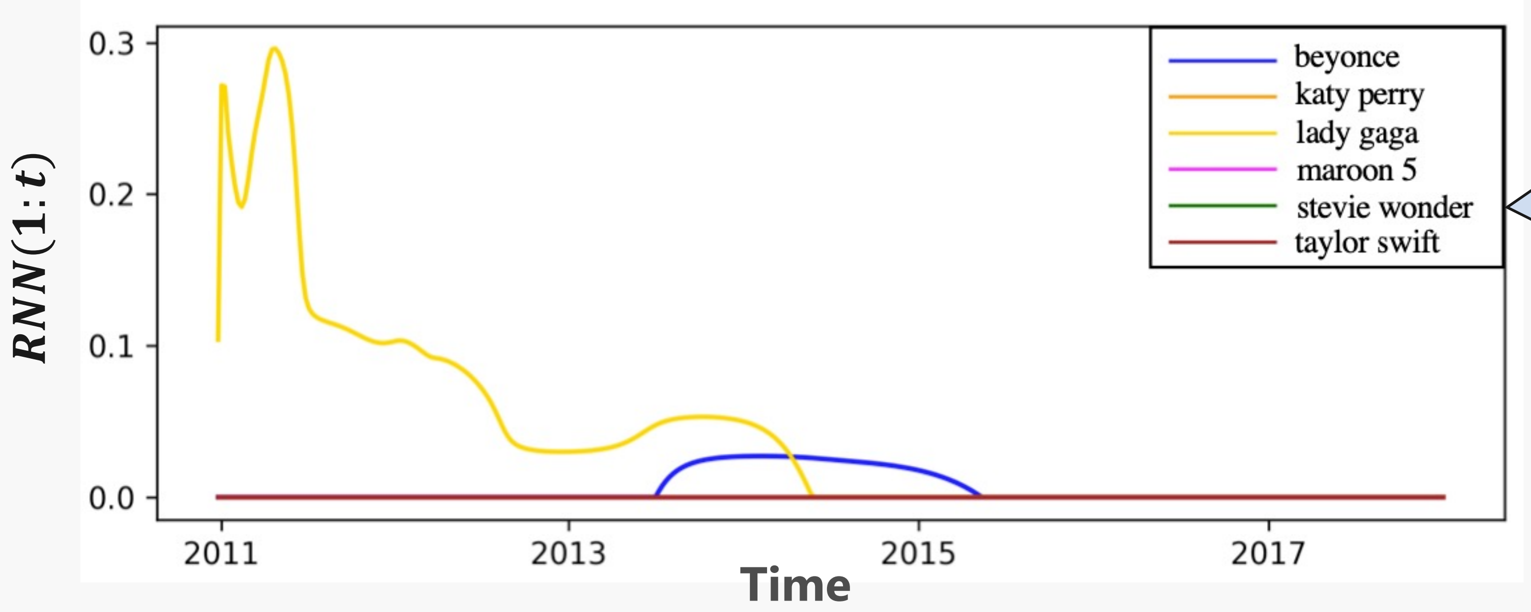
Our model represents the interaction between locations by **Recurrent Neural Network**

By applying a neural network to apart of our mathematical model, we expect to achieve both **flexible modeling and high explainability.**

FLUXCUBE: $$\frac{\partial x_{tij}}{\partial t} = \boldsymbol{f}\left(x_{tij} | \boldsymbol{\chi}_{\boldsymbol{t},\boldsymbol{i},:}\right) + \boxed{g\left(x_{tij} | \boldsymbol{\chi}_{t}, \boldsymbol{t}\right)}$$

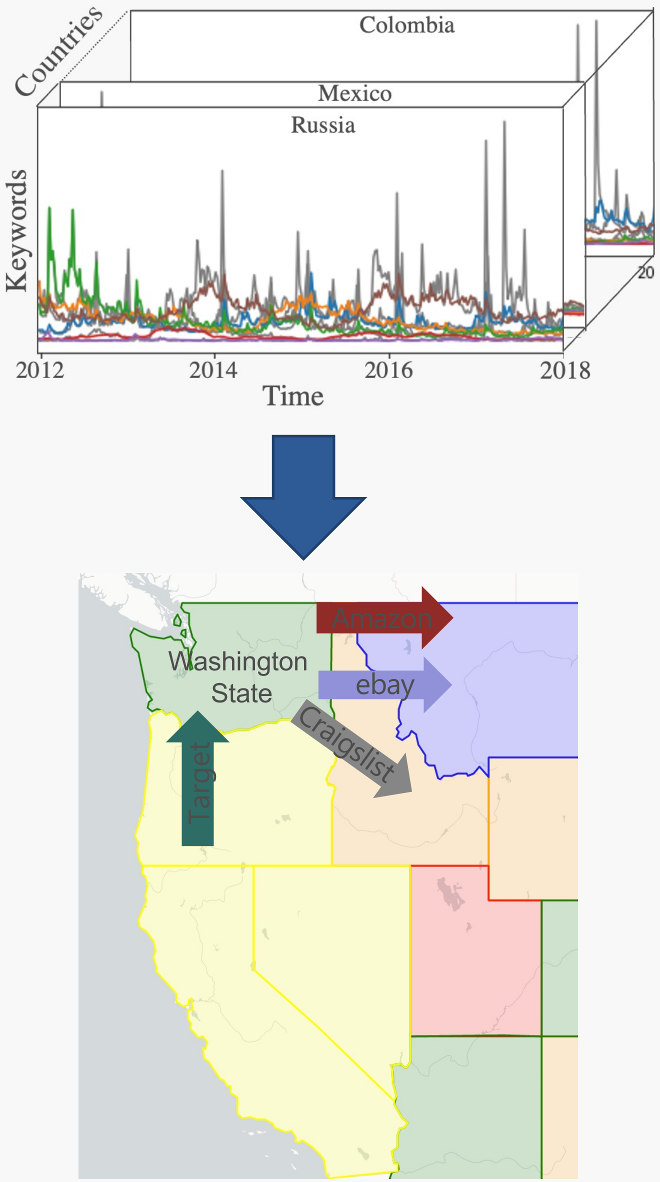
$$g\left(x_{tij} | \boldsymbol{\chi}_{t}, \boldsymbol{t}\right) = \sum RNN(1: t) \odot \boldsymbol{\chi}_{\boldsymbol{t}}$$

The output value of RNN represents **the contribution of the popularity** of each keyword between locations.



The contribution of the popularity from Canada to France

$$g(x_{tij}|\chi_t, t) = \sum \boxed{RNN(1:t)} \odot \chi_t$$



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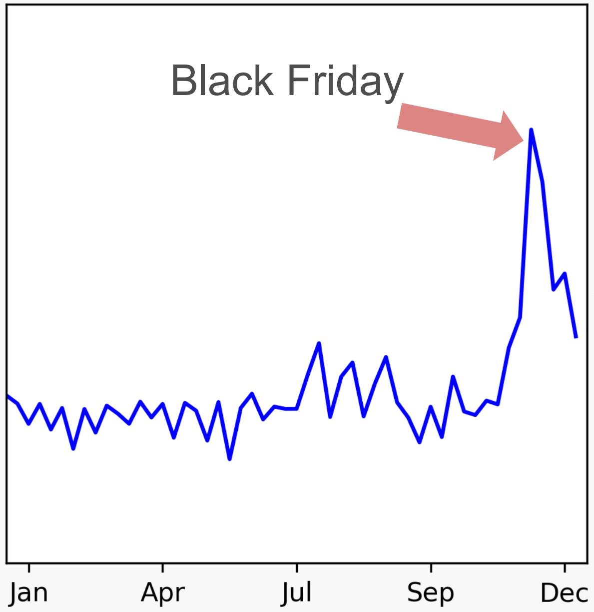
$$x_{t+1ij} = F\left(\frac{\partial x_{tij}}{\partial t} + x_{tij}\right)$$

Finding hidden seasonality

Online users change their behavior according **to seasonal events**, such as Christmas and Black Friday.

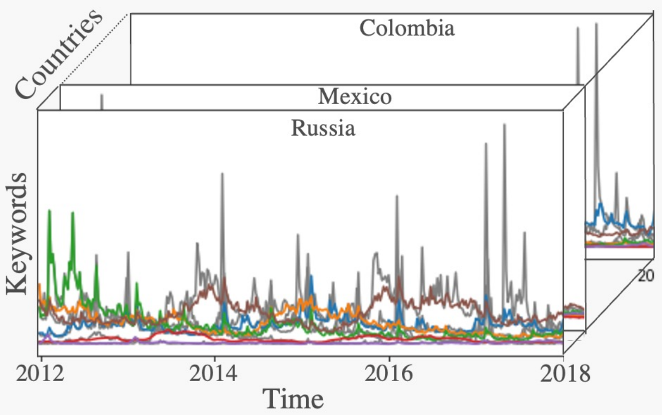


$$x_{t+1ij} = F\left(\frac{\partial x_{tij}}{\partial t} + x_{tij}\right)$$

Seasonality Weight
e.g., p = 52 weeks

$$= \left(1 + \boxed{\left[S_{t \bmod p}\right]_{ij}}\right) \odot \left(\frac{\partial x_{tij}}{\partial t} + x_{tij}\right)$$

FLUXCUBE



Input: $\chi = \{\boldsymbol{x_{tij}}\}$

Reaction term — Diffusion term

$$\frac{\partial x_{tij}}{\partial t} = \boldsymbol{f}\left(x_{tij} \middle| \boldsymbol{\chi_{t,i,:}}\right) + g\left(x_{tij} \middle| \boldsymbol{\chi_t}, \boldsymbol{t}\right)$$

$$x_{t+1ij} = F\left(\frac{\partial x_{tij}}{\partial t} + x_{tij}\right)$$

Regression term — Sparse term

Loss Function $\boxed{\|\chi^c - \hat{\chi}\|^2} + \boxed{\alpha \sum \|D\|^2 + \beta \sum \|S\|^2}$

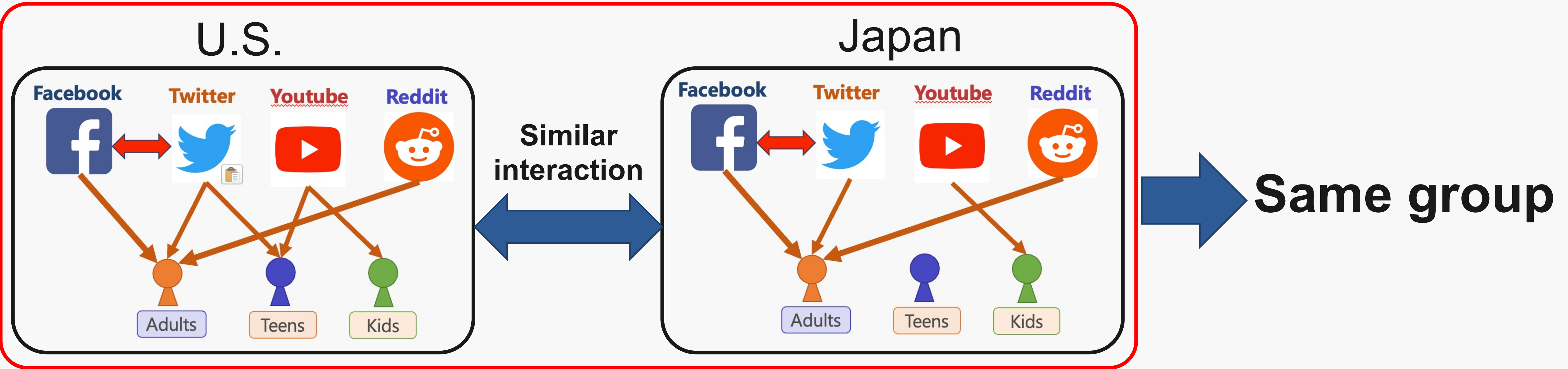
- It is difficult to **infer** **interactions between many areas** due to computational costs.

Country Grouping

- It is difficult to **infer interactions between many areas** due to computational costs.

Our solution:

Before training, grouping similar areas into same group



Reaction term

$$\textbf{FLUXCUBE:}\quad \frac{\partial x_{tij}}{\partial t} = \boxed{\boldsymbol{f}\left(x_{tij} \mid \boldsymbol{\chi}_{t,i,:}\right)} + g\left(x_{tij} \mid \boldsymbol{\chi}_t, \boldsymbol{t}\right)$$

$$\boldsymbol{f}\left(x_{tij} \mid \boldsymbol{\chi}_{t,i,:}\right) = a_j \boldsymbol{\chi}_{t,i,j}\left(1 - \frac{\sum_{j'} c_{jj'} x_{tij'}}{b_j}\right)$$

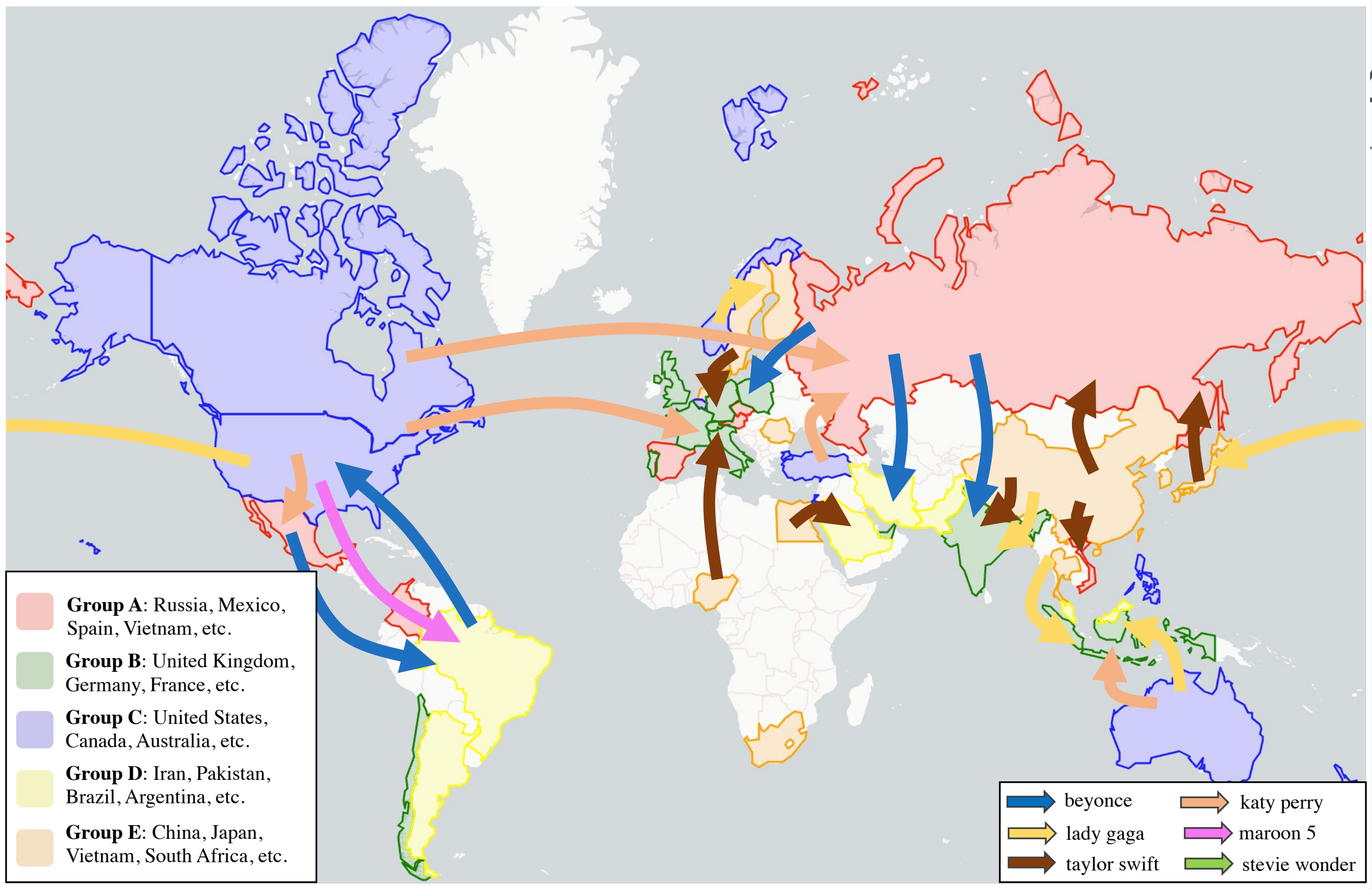
$$\boxed{g^1, \ldots g^{d^l}} = \text{K-means}\left(\text{UMAP}\boxed{\left(\boldsymbol{a}^i, \boldsymbol{b}^i, \boldsymbol{C}^i\right)}\right), \boxed{i = [1, \ldots, L]}$$

Grouping each areas

Parameters in Reaction term of each country

Number of countries

Country Grouping



We find suitable number of area groups (d^l) by Model Description Cost (MDL)

$$\boxed{g^1, \dots g^{d^l}} = \text{K-means}\left(\mathrm{UMAP}\boxed{\left(\boldsymbol{a}^i, \boldsymbol{b}^i, \boldsymbol{C}^i\right)}\right), \boxed{i = [1, \dots, L]}$$

Grouping each areas

Parameters in Reaction term of each country

Number of countries

Experimental Settings

- Evaluate the forecasting score in 13, 26, 52 weeks ahead
- Evaluation Metrics
  - RMSE, MAE: Smaller value indicating better performance

Dataset

- Two types of Google Trend data, which contained weekly web search volumes collected for about 10 years

ID	Dataset	Query
US#1	E-commerce	Amazon/Apple/BestBuy/Costco/Craigslist/Ebay/Homedepot/Kohls/Macys/Target/Walmart
US#2	VoD	AppleTV/ESPN/HBO/Hulu/Netflix/Sling/Vudu/YouTube
US#3	Sweets	Cake/Candy/Chocolate/Cookie/Cupcake/Gum/Icecream/Pie/Pudding
US#4	Facilities	Aquarium/Bookstore/Gym/Library/Museum/Theater/Zoo
World#1	Music	Beyonce/KatyPerry/LadyGaga/Maroon5/StevieWonder/TaylorSwift
World#2	SNS	Facebook/LINE/Slack/Snapchat/Twitter/Viber/WhatsApp
World#3	Apparel	Gap/H&M/Primark/Uniqlo/Zara

Experimental Performance

Dataset	Model	13 weeks RMSE	13 weeks MAE	26 weeks RMSE	26 weeks MAE	52 weeks RMSE	52 weeks MAE
US#1	EcoWeb	0.1470	0.0950	0.1554	0.1082	0.1654	0.1197
	SMF	0.0869	0.0620	0.0910	0.0654	0.1012	0.0674
	DeepAR	0.1003	0.0634	0.1302	0.0907	0.1385	0.1014
	GRU	0.1723	0.1175	0.1924	0.1374	0.2059	0.1525
	Informer	0.1477	0.1045	0.1375	0.0985	0.1575	0.1111
	FluxCube	**0.0478**	**0.0257**	**0.0574**	**0.0323**	**0.0631**	**0.0365**
US#2	EcoWeb	0.1440	0.1133	0.1981	0.1621	0.1920	0.1684
	SMF	0.0621	0.0445	0.0713	0.0522	0.0760	0.0529
	DeepAR	0.1471	0.1026	0.1781	0.1314	0.1906	0.1474
	GRU	0.1518	0.1171	0.1619	0.1231	0.1683	0.1440
	Informer	0.1277	0.0878	0.1292	0.0876	0.1436	0.1012
	FluxCube	**0.0245**	**0.0130**	**0.0276**	**0.0156**	**0.0310**	**0.0181**
US#3	EcoWeb	0.1555	0.1208	0.1730	0.1384	0.1754	0.1369
	SMF	0.0276	0.0186	0.0281	0.0170	0.0281	0.0190
	DeepAR	0.1107	0.0753	0.1267	0.0833	0.1309	0.0908
	GRU	0.1300	0.0869	0.1368	0.9843	0.1368	0.0939
	Informer	0.1322	0.0954	0.1311	0.0946	0.1279	0.0914
	FluxCube	**0.0200**	**0.0121**	**0.0222**	**0.0136**	**0.0238**	**0.0148**

Dataset	Model	13 weeks RMSE	13 weeks MAE	26 weeks RMSE	26 weeks MAE	52 weeks RMSE	52 weeks MAE
World#1	EcoWeb	0.1259	0.0831	0.1422	0.1034	0.2101	0.1460
	SMF	0.0936	0.0783	0.0901	0.0602	0.1087	0.0787
	DeepAR	0.0900	0.0636	0.0929	0.0681	0.1395	0.0972
	GRU	0.0633	0.0452	0.0718	0.0501	0.0823	0.0572
	Informer	0.0704	0.0423	0.0719	0.0416	0.0738	0.0446
	FluxCube	**0.0454**	**0.0274**	**0.0477**	**0.0286**	**0.0546**	**0.0331**
World#2	EcoWeb	0.0908	0.0300	0.1089	0.0570	0.1353	0.0742
	SMF	0.0841	0.0436	0.0799	0.0454	0.0826	0.0480
	DeepAR	0.0374	**0.0098**	**0.0585**	0.0199	0.0643	0.0209
	GRU	0.0401	0.0159	0.0588	**0.0174**	0.0739	0.0254
	Informer	**0.0371**	0.0159	0.0595	0.0196	**0.0642**	**0.0208**
	FluxCube	0.0704	0.0271	0.0711	0.0304	0.0831	0.0351
World#3	EcoWeb	0.0523	0.0208	0.0626	0.0200	0.1080	0.0293
	SMF	0.0206	0.0111	0.0289	0.0160	0.0254	0.0195
	DeepAR	0.0211	0.0110	0.0275	0.0099	0.0613	0.0214
	GRU	0.0191	0.0090	0.0217	**0.0096**	0.00235	0.0115
	Informer	0.0223	0.0105	0.0226	0.0105	**0.0214**	0.0108
	FluxCube	**0.0176**	**0.0085**	**0.0214**	**0.0096**	0.0221	**0.0100**

Experimental Performance

Dataset	Model	13 weeks RMSE	13 weeks MAE	26 weeks RMSE	26 weeks MAE	52 weeks RMSE	52 weeks MAE
US#1	EcoWeb	0.1470	0.0950	0.1554	0.1082	0.1654	0.1197
	SMF	0.0869	0.0620	0.0910	0.0654	0.1012	0.0674
	DeepAR	0.1003	0.0634	0.1302	0.0907	0.1385	0.1014
	GRU	0.1723	0.1175	0.1924	0.1374	0.2059	0.1525
	Informer	0.1477	0.1045	0.1375	0.0985	0.1575	0.1111
	FluxCube	**0.0478**	**0.0257**	**0.0574**	**0.0323**	**0.0631**	**0.0365**
US#2	EcoWeb	0.1440	0.1133	0.1981	0.1621	0.1920	0.1684
	SMF	0.0621	0.0445	0.0713	0.0522	0.0760	0.0529
	DeepAR	0.1471	0.1026	0.1781	0.1314	0.1906	0.1474
	GRU	0.1518	0.1171	0.1619	0.1231	0.1683	0.1440
	Informer	0.1277	0.0878	0.1292	0.0876	0.1436	0.1012
	FluxCube	**0.0245**	**0.0130**	**0.0276**	**0.0156**	**0.0310**	**0.0181**
US#3	EcoWeb	0.1555	0.1208	0.1730	0.1384	0.1754	0.1369
	SMF	0.0276	0.0186	0.0281	0.0170	0.0281	0.0190
	DeepAR	0.1107	0.0753	0.1267	0.0833	0.1309	0.0908
	GRU	0.1300	0.0869	0.1368	0.9843	0.1368	0.0939
	Informer	0.1322	0.0954	0.1311	0.0946	0.1279	0.0914
	FluxCube	**0.0200**	**0.0121**	**0.0222**	**0.0136**	**0.0238**	**0.0148**

Dataset	Model	13 weeks RMSE	13 weeks MAE	26 weeks RMSE	26 weeks MAE	52 weeks RMSE	52 weeks MAE
World#1	EcoWeb	0.1259	0.0831	0.1422	0.1034	0.2101	0.1460
	SMF	0.0936	0.0783	0.0901	0.0602	0.1087	0.0787
	DeepAR	0.0900	0.0636	0.0929	0.0681	0.1395	0.0972
	GRU	0.0633	0.0452	0.0718	0.0501	0.0823	0.0572
	Informer	0.0704	0.0423	0.0719	0.0416	0.0738	0.0446
	FluxCube	**0.0454**	**0.0274**	**0.0477**	**0.0286**	**0.0546**	**0.0331**
World#2	EcoWeb	0.0908	0.0300	0.1089	0.0570	0.1353	0.0742
	SMF	0.0841	0.0436	0.0799	0.0454	0.0826	0.0480
	DeepAR	0.0374	**0.0098**	**0.0585**	0.0199	0.0643	0.0209
	GRU	0.0401	0.0159	0.0588	**0.0174**	0.0739	0.0254
	Informer	**0.0371**	0.0159	0.0595	0.0196	**0.0642**	**0.0208**
	FluxCube	0.0704	0.0271	0.0711	0.0304	0.0831	0.0351
World#3	EcoWeb	0.0523	0.0208	0.0626	0.0200	0.1080	0.0293
	SMF	0.0206	0.0111	0.0289	0.0160	0.0254	0.0195
	DeepAR	0.0211	0.0110	0.0275	0.0099	0.0613	0.0214
	GRU	0.0191	0.0090	0.0217	**0.0096**	0.00235	0.0115
	Informer	0.0223	0.0105	0.0226	0.0105	**0.0214**	0.0108
	FluxCube	**0.0176**	**0.0085**	**0.0214**	**0.0096**	0.0221	**0.0100**

Experimental Performance

Dataset	Model	13 weeks		26 weeks		52 weeks	
		RMSE	MAE	RMSE	MAE	RMSE	MAE
US#1	EcoWeb	0.1470	0.0950	0.1554	0.1082	0.1654	0.1197
	SMF	0.0869	0.0620	0.0910	0.0654	0.1012	0.0674
	DeepAR	0.1003	0.0634	0.1302	0.0907	0.1385	0.1014
	GRU	0.1723	0.1175	0.1924	0.1374	0.2059	0.1525
	Informer	0.1477	0.1045	0.1375	0.0985	0.1575	0.1111
	FluxCube	**0.0478**	**0.0257**	**0.0574**	**0.0323**	**0.0631**	**0.0365**
US#2	EcoWeb	0.1440	0.1133	0.1981	0.1621	0.1920	0.1684
	SMF	0.0621	0.0445	0.0713	0.0522	0.0760	0.0529
	DeepAR	0.1471	0.1026	0.1781	0.1314	0.1906	0.1474
	GRU	0.1518	0.1171	0.1619	0.1231	0.1683	0.1440
	Informer	0.1277	0.0878	0.1292	0.0876	0.1436	0.1012
	FluxCube	**0.0245**	**0.0130**	**0.0276**	**0.0156**	**0.0310**	**0.0181**
US#3	EcoWeb	0.1555	0.1208	0.1730	0.1384	0.1754	0.1369
	SMF	0.0276	0.0186	0.0281	0.0170	0.0281	0.0190
	DeepAR	0.1107	0.0753	0.1267	0.0833	0.1309	0.0908
	GRU	0.1300	0.0869	0.1368	0.9843	0.1368	0.0939
	Informer	0.1322	0.0954	0.1311	0.0946	0.1279	0.0914
	FluxCube	**0.0200**	**0.0121**	**0.0222**	**0.0136**	**0.0238**	**0.0148**

Dataset	Model	13 weeks		26 weeks		52 weeks	
		RMSE	MAE	RMSE	MAE	RMSE	MAE
World#1	EcoWeb	0.1259	0.0831	0.1422	0.1034	0.2101	0.1460
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	GRU	0.0633	0.0452	0.0718	0.0501	0.0823	0.0572
	Informer	0.0704	0.0423	0.0719	0.0416	0.0738	0.0446
	FluxCube	**0.0454**	**0.0274**	**0.0477**	**0.0286**	**0.0546**	**0.0331**
World#2	EcoWeb	0.0908	0.0300	0.1089	0.0570	0.1353	0.0742
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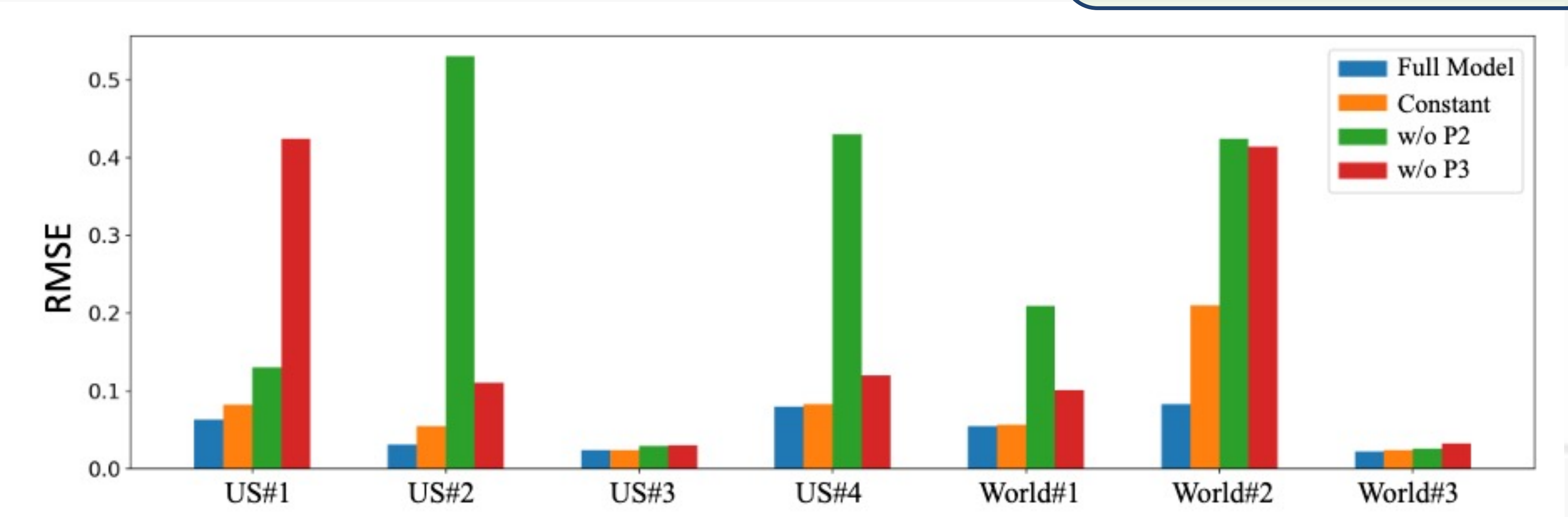
	DeepAR	0.0374	**0.0098**	**0.0585**	0.0199	0.0643	0.0209
	GRU	0.0401	0.0159	0.0588	**0.0174**	0.0739	0.0254
	Informer	**0.0371**	0.0159	0.0595	0.0196	**0.0642**	**0.0208**
	FluxCube	0.0704	0.0271	0.0711	0.0304	0.0831	0.0351
World#3	EcoWeb	0.0523	0.0208	0.0626	0.0200	0.1080	0.0293
	SMF	0.0206	0.0111	0.0289	0.0160	0.0254	0.0195
	DeepAR	0.0211	0.0110	0.0275	0.0099	0.0613	0.0214
	GRU	0.0191	0.0090	0.0217	**0.0096**	0.00235	0.0115
	Informer	0.0223	0.0105	0.0226	0.0105	**0.0214**	0.0108
	FluxCube	**0.0176**	**0.0085**	**0.0214**	**0.0096**	0.0221	**0.0100**

Ablation Study

$$x_{t+1ij} = \boxed{F}\left(\frac{\partial x_{tij}}{\partial t} + x_{tij}\right)$$

$$\frac{\partial x_{tij}}{\partial t} = \boldsymbol{f}\left(x_{tij} | \boldsymbol{\chi}_{t,i,:}\right) + \boxed{g\left(x_{tij} | \boldsymbol{\chi}_t, \boldsymbol{t}\right)}$$



Full Model

Replace g() with constant value

Removal: g()

Removal Seasonal

Ablation Study

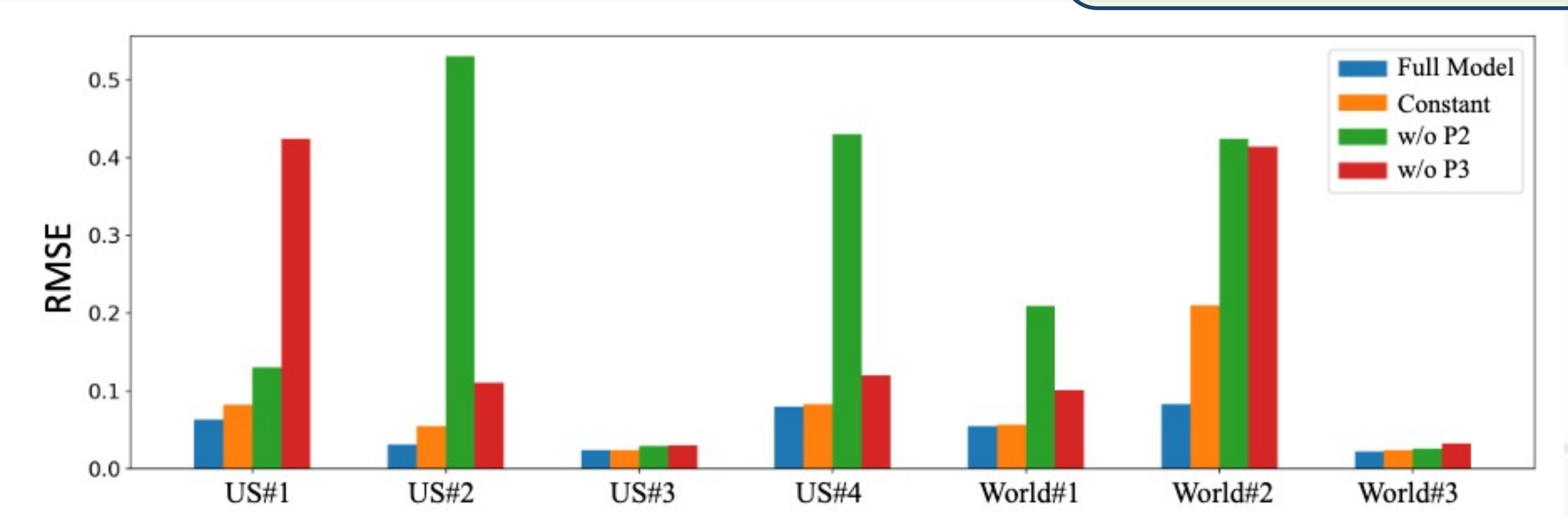
$$x_{t+1ij} = \boxed{F}\left(\frac{\partial x_{tij}}{\partial t} + x_{tij}\right)$$

$$\frac{\partial x_{tij}}{\partial t} = \boldsymbol{f}\left(x_{tij}|\boldsymbol{\chi}_{\boldsymbol{t},\boldsymbol{i},:}\right) + \boxed{g\left(x_{tij}|\boldsymbol{\chi}_{t}, \boldsymbol{t}\right)}$$

$$g\left(x_{tij}|\boldsymbol{\chi}_{t}, \boldsymbol{t}\right) = \sum RNN(1{:}\, t) \odot \boldsymbol{\chi}_{t}$$

$$\Downarrow$$

$$\boxed{\boldsymbol{\alpha} \odot \boldsymbol{\chi}_{t}}$$



Full Model

Replace g() with constant value

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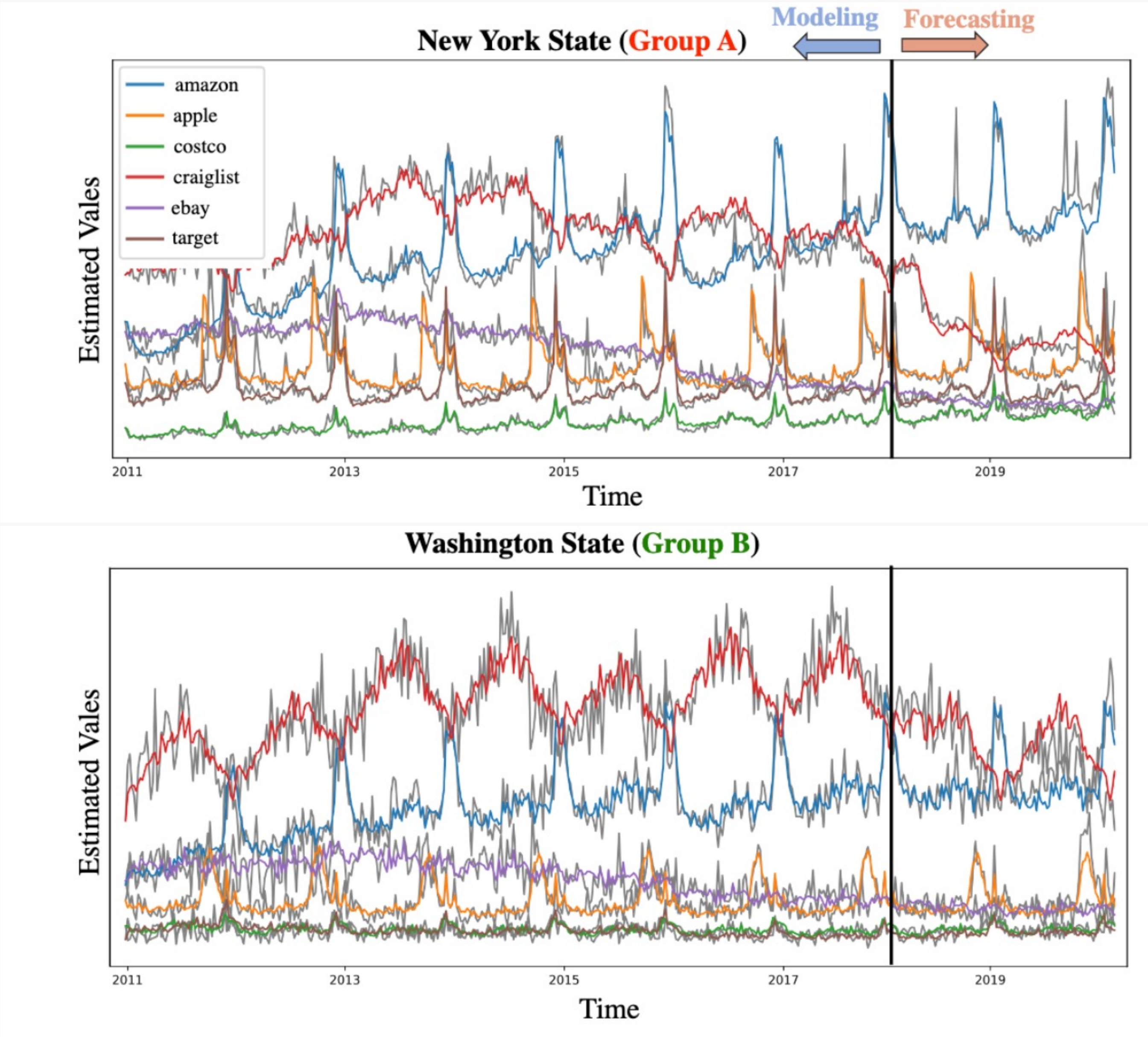
Case study1: Vod

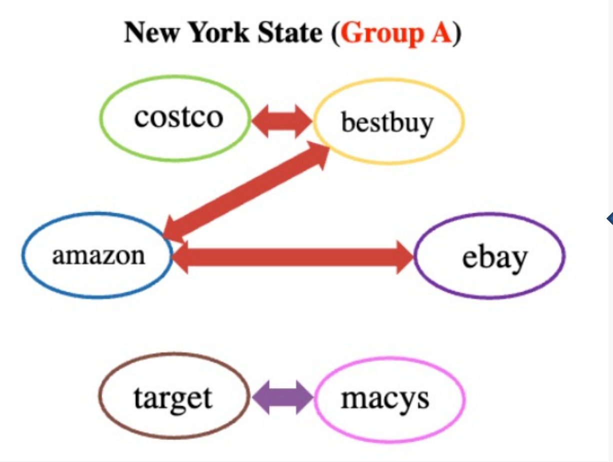


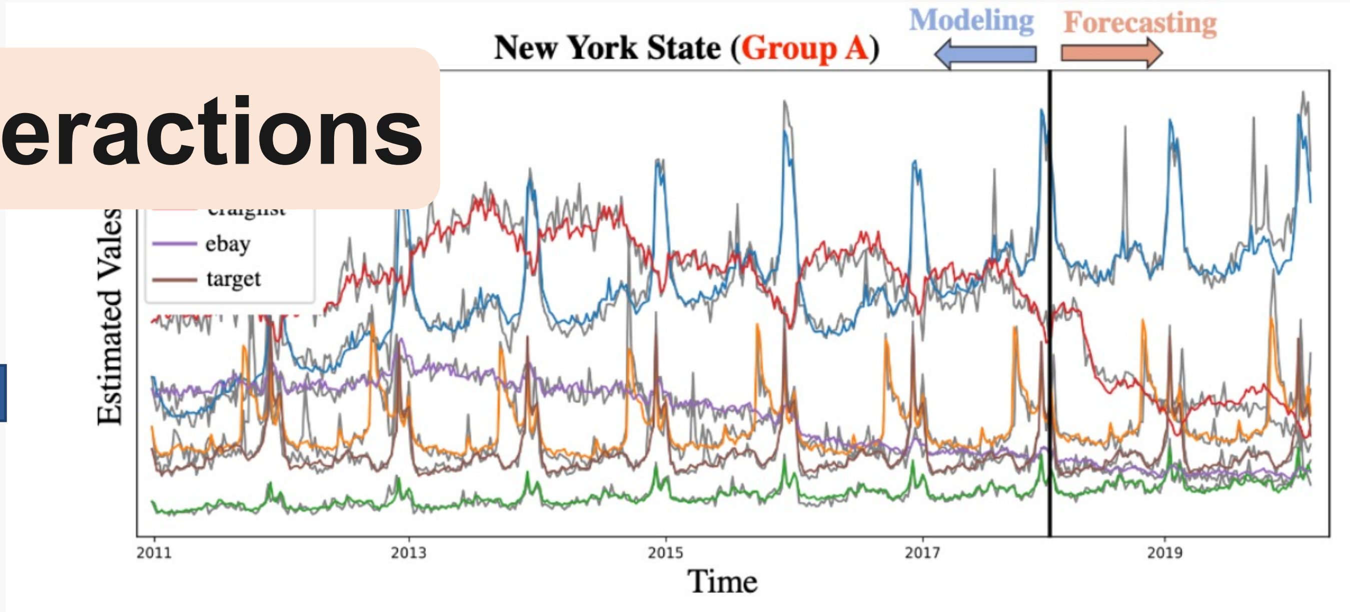
Keyword List

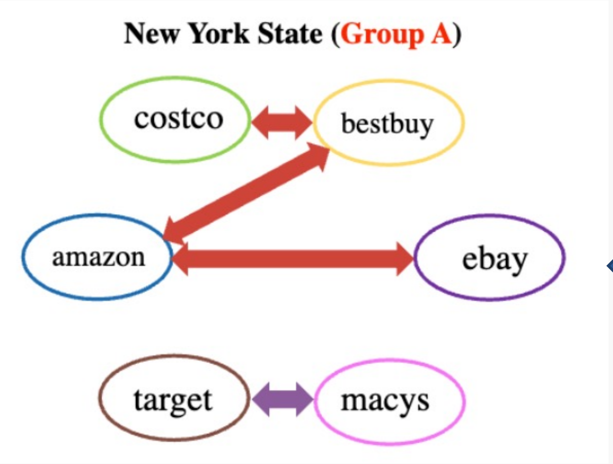
AppleTV / ESPN / HBO / Hulu / Netflix
Sling / Vudu / Youtube

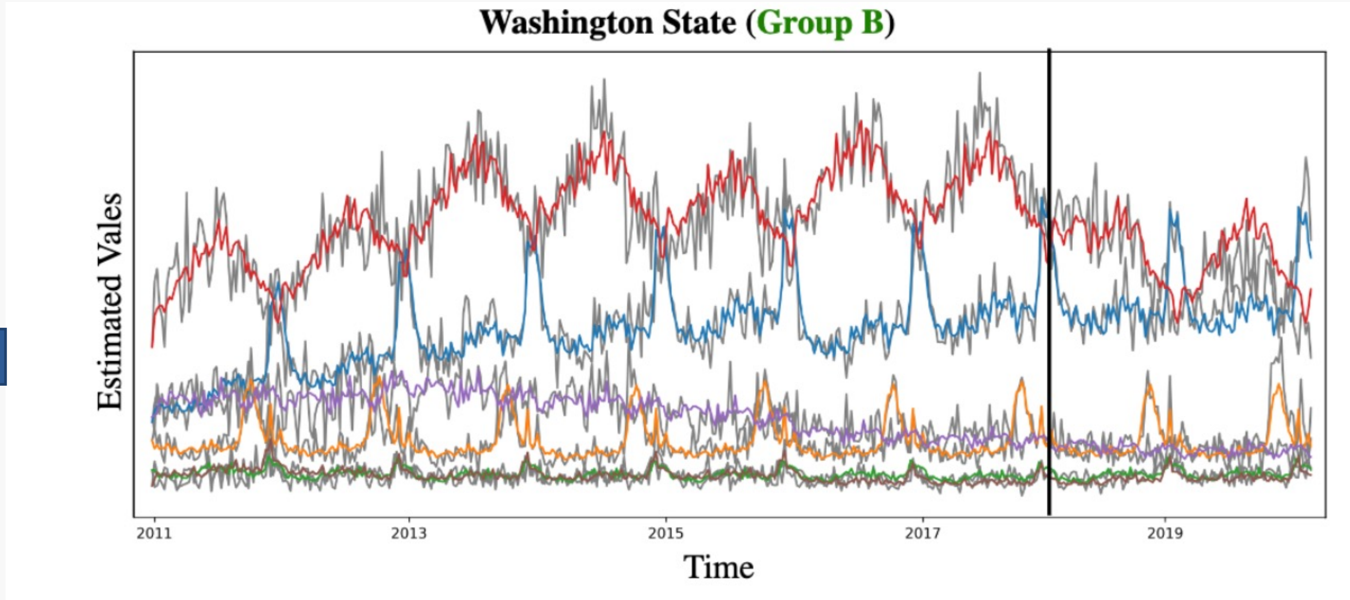
Case study1: Vod

Interactions



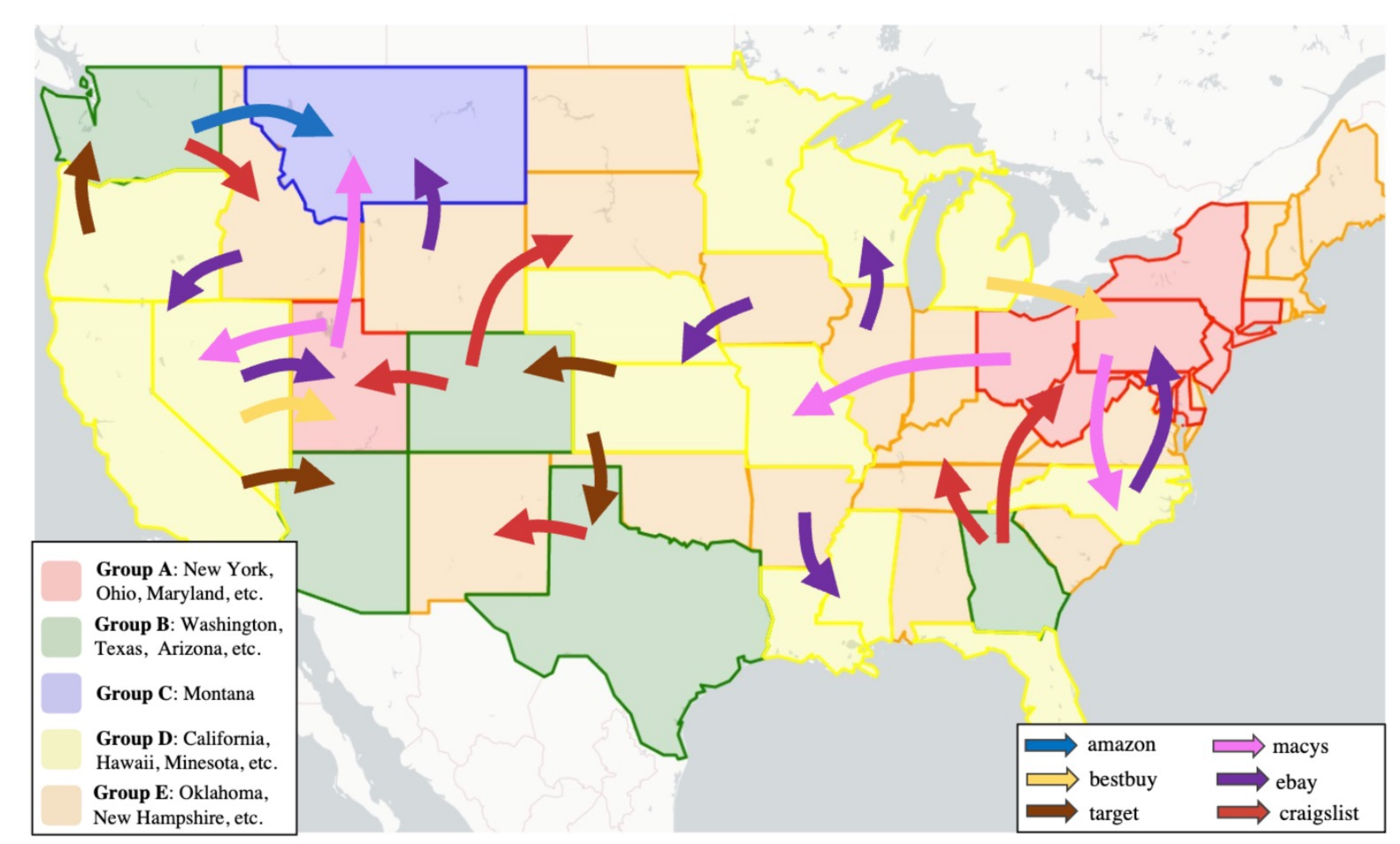


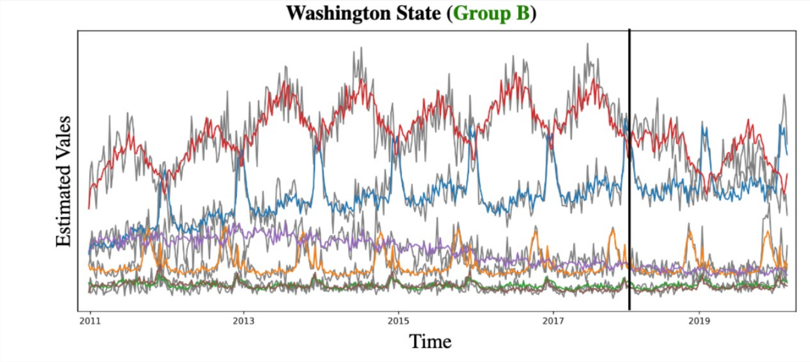


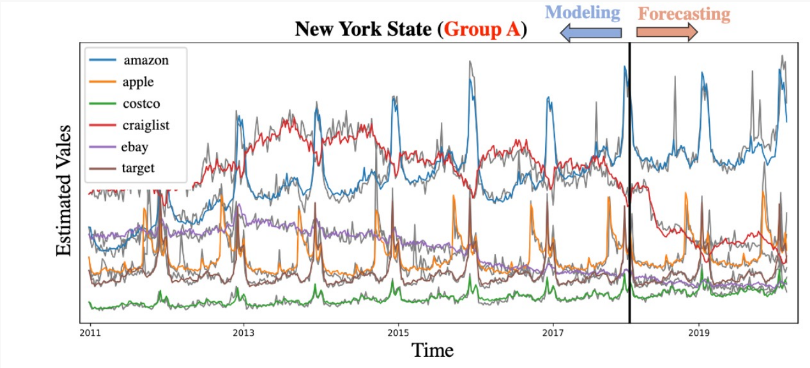


Case study1: Vod

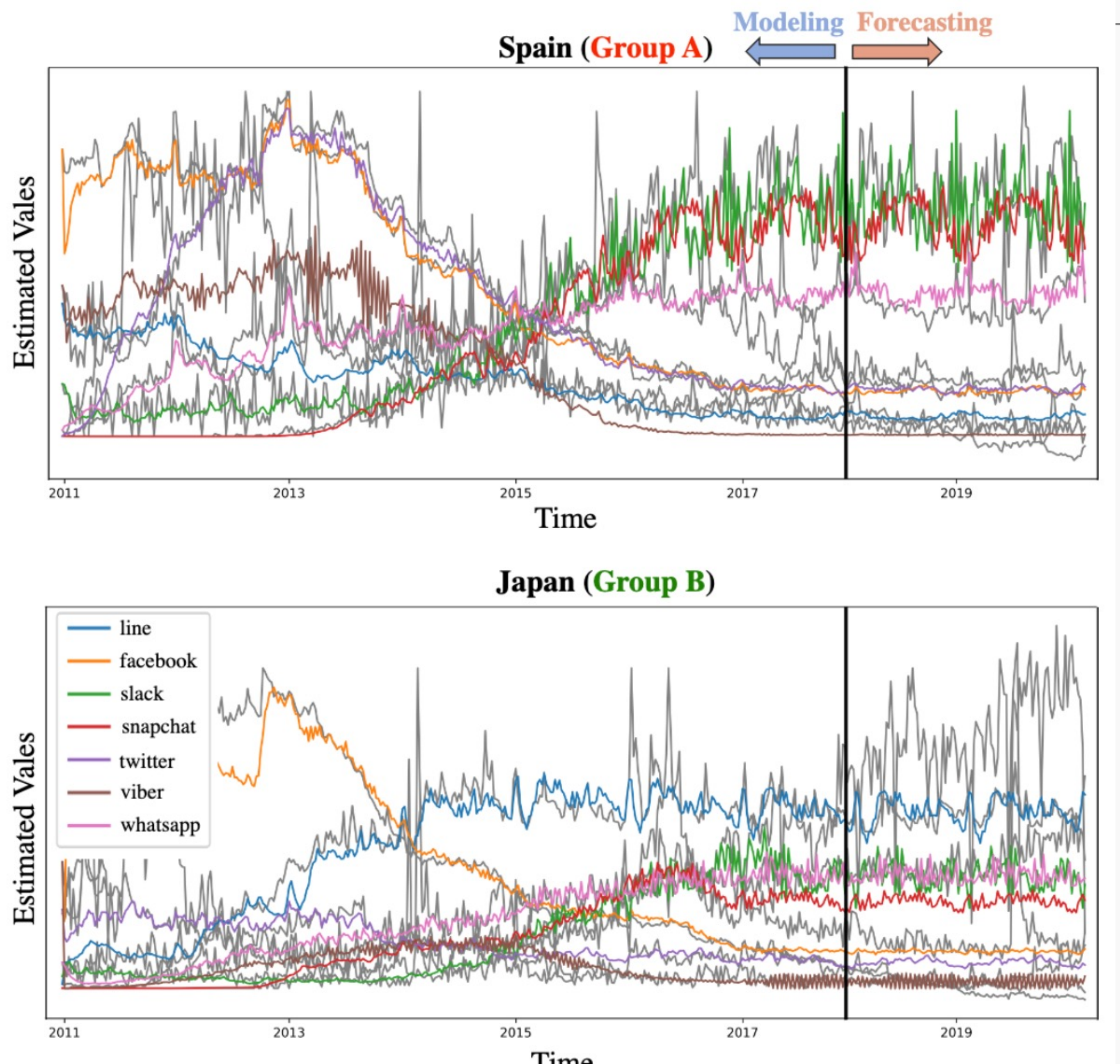
Influential flow







Case study2: Music

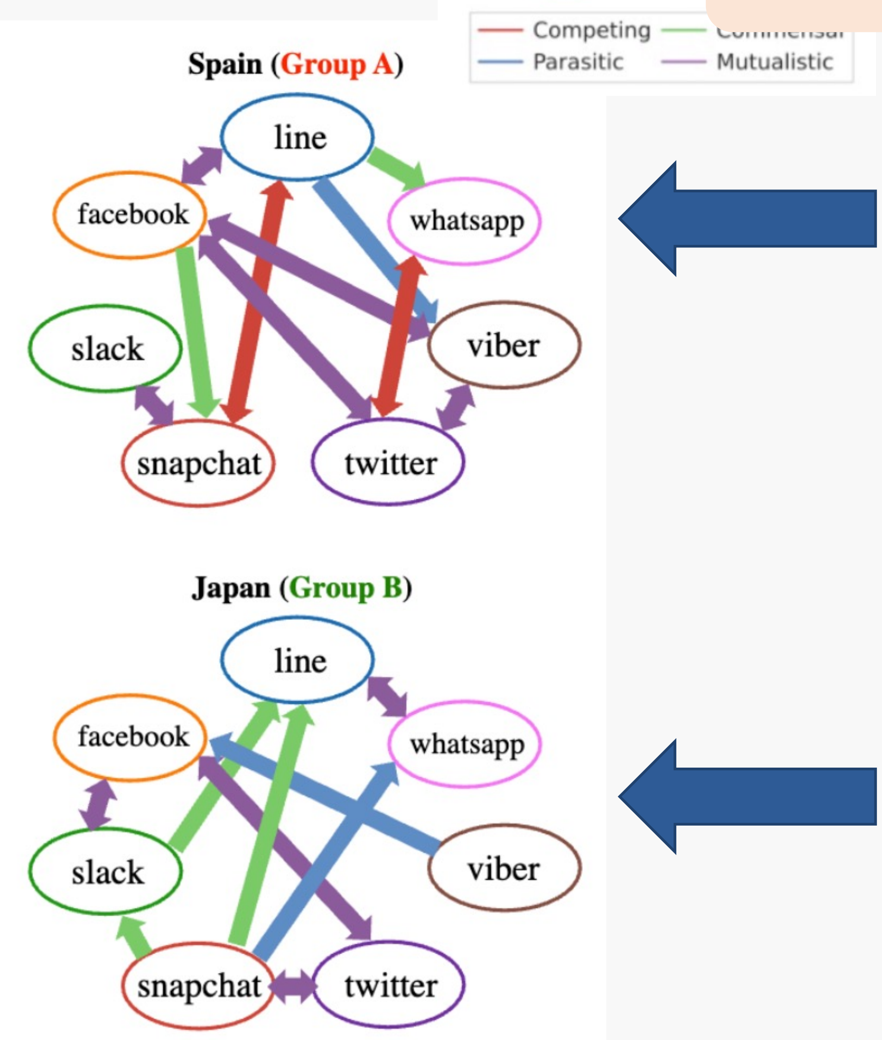


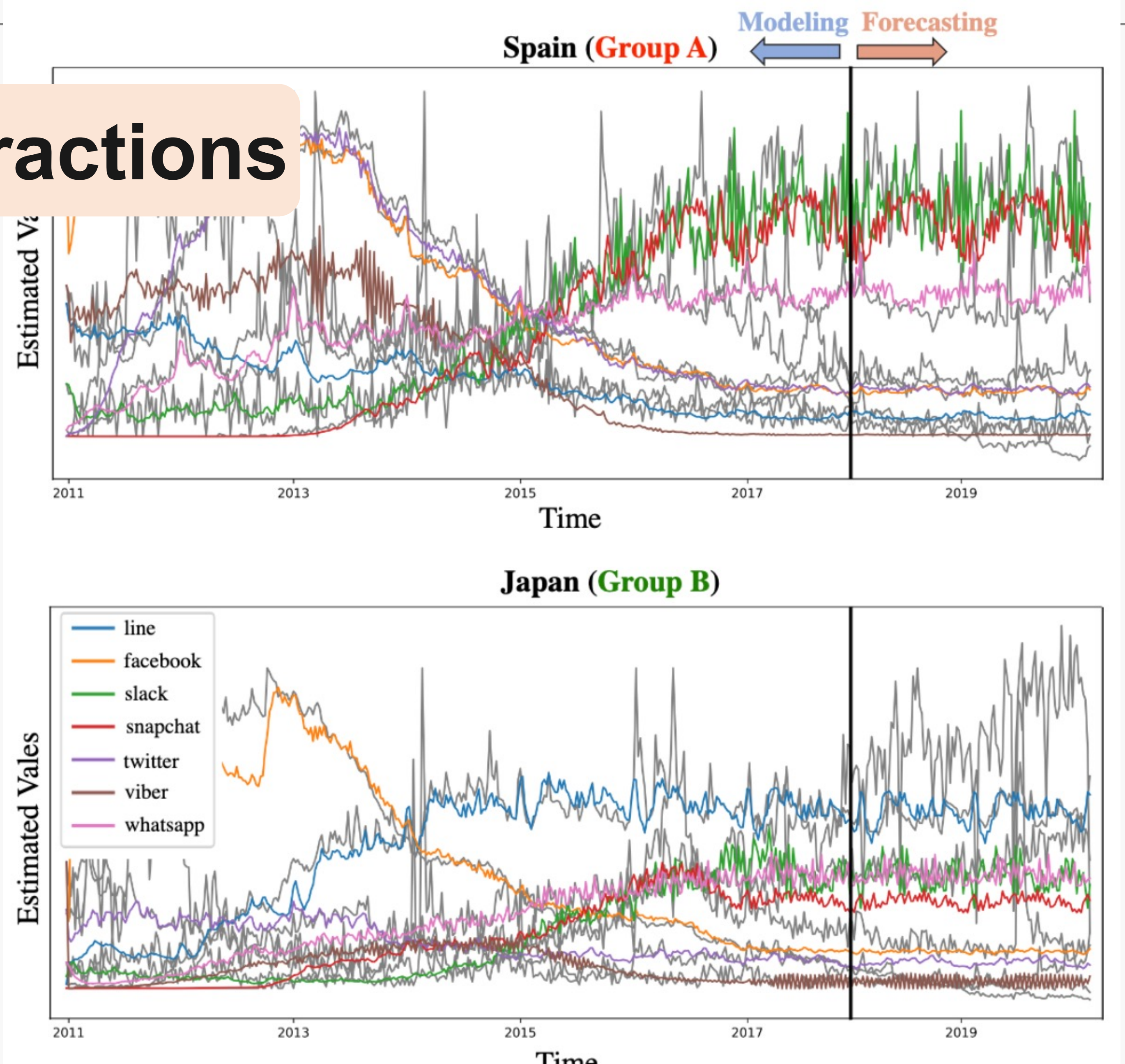
Keyword List

Beyonce/KatyPerry/LadyGaga/Maroon5/
StevieWonder/TaylorSwift

Case study2: Music

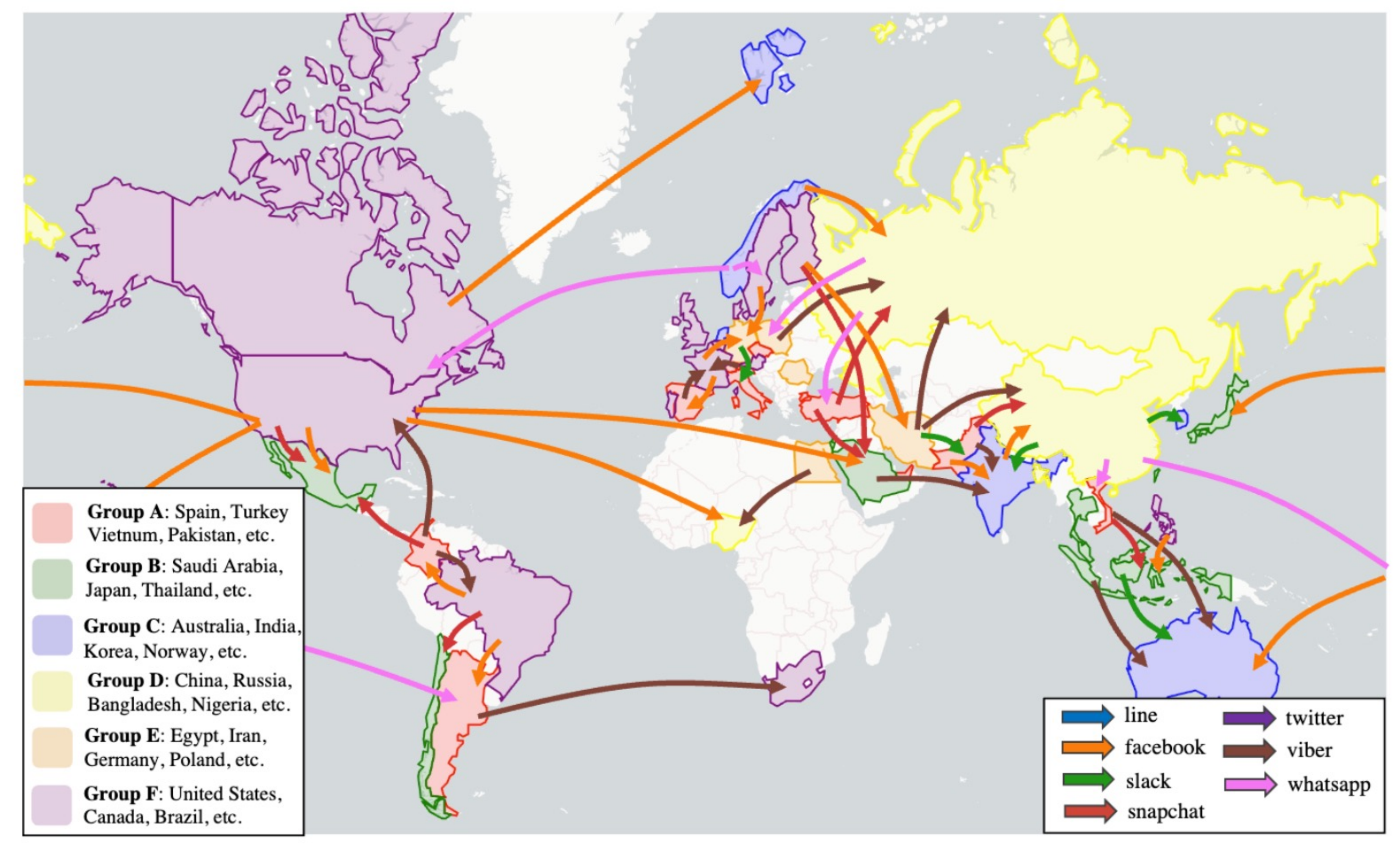
Interactions

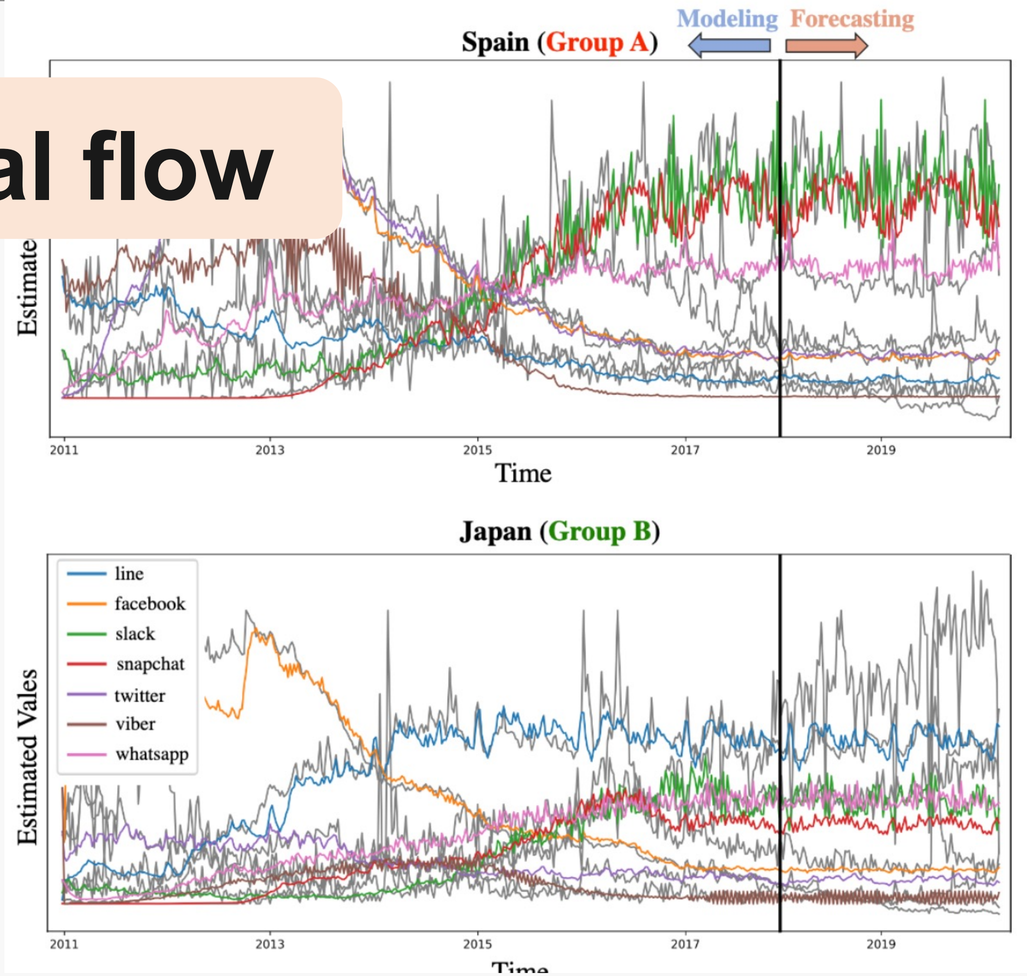




Case study2: Music

Influential flow





- **FLUXCUBE:** an effective modeling and forecasting method based on reaction-diffusion and ecological systems. It can recognize trends, seasonality and interactions in input observations by extracting their latent dynamic systems.
- Proposed model achieves higher accuracy in Google Trends Datasets by capturing the latent dynamics .
- It provides the latent interactions and the influence flows hidden behind observational data in a human-interpretable form.