Data Driven Methods for Disease Forecasting

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Traditional Approaches: Computational Epidemiology

- Computatational models (ode, etc.)
- Population level vs Network level
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- Effectiveness depends on Good Surveillance data.
- Surveillance often delayed
- Surveillance often updated over time

Epidemiology in data driven world

- Surrogate information can be found in social medium
- Physical indicators can also have causal effects on diseases.
- Can complement traidtionl surveillance
  - Provide real-time estimates
  - Provide robust estimates of already published data

Example Problems (see www.dac.cs.vt.edu)

- Predicting Hantavirus outbreaks from news articles*
- Chikungunya Spread detection
- Influenza like Illness (ILI) forecasting.

* Saurav Ghosh et al. "Forecasting Rare Disease Outbreaks with Spatio-temporal Topic Models". In: *NIPS 2013 workshop on Topic Models*. 2013

Problem Overview

Near-horizon forecast of ILI case counts at country level*

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- Predicting weekly Influenza-like-illness (ILI) case counts for 15 Latin American countries
- Investigating different open source data-streams as possible surrogate indicators of ILI

* Prithwish Chakraborty et al. "Forecasting a Moving Target: Ensemble Models for ILI Case Count Predictions". In: *Proceedings of the 2014 SIAM International Conference on Data Mining, Philadelphia, Pennsylvania, USA, April 24-26, 2014*. 2014, pp. 262–270

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1. Real-time prospective study - most studies till this paper were retrospective.

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4. Accounting for uncertainties in the official surveillance estimates
5. Investigate importance of different sources - Ablation test

1. Introduction
   - Motivation: Data driven epidemiology
   - Data driven Epidemiology: Problems
   - Main Goals

2. Methods
   - Data Sources
   - Custom User Keywords
   - Matrix Factorization using Nearest Neighborhood
   - Model level vs Data level fusion

3. Instability Analysis

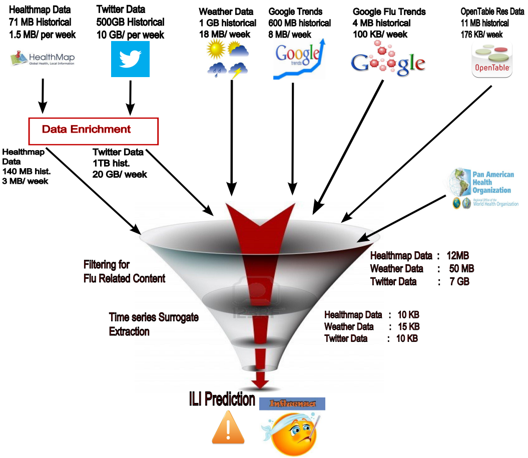
4. Ablation Test

5. Conclusion
   - Extending to other sources: Opentable
   - Summary

Key Ingredients

- Better Data - extract information from external indicators.
- Better Models - handle non-linearity.
- Handle Real world noise

Overall Framework



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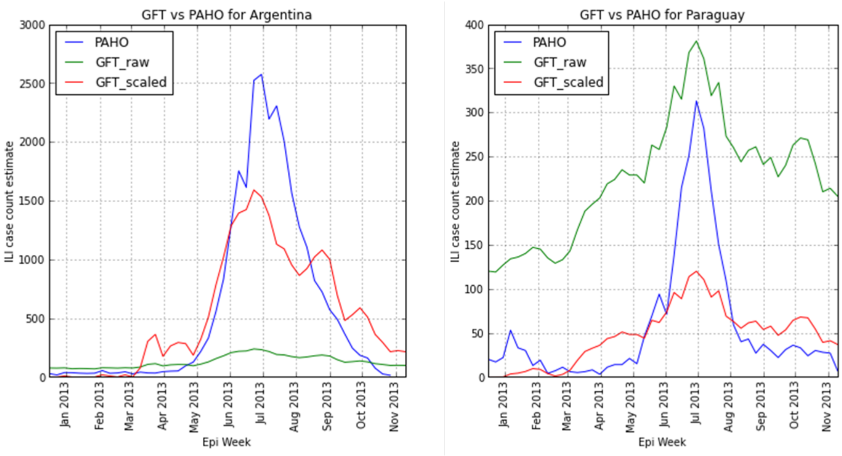
- Physical indicators
- Misc. Indicators
  1. Opentable reservations

Google Flu Trends



Finding Custom user keyword dictionary

A multiple step process :

- Started with a seed set of keywords from experts.
  - Seed set contains words in Spanish, Portuguese, and English.
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  - Used Google Correlate to find words with search history correlated with ILI incidence curve.
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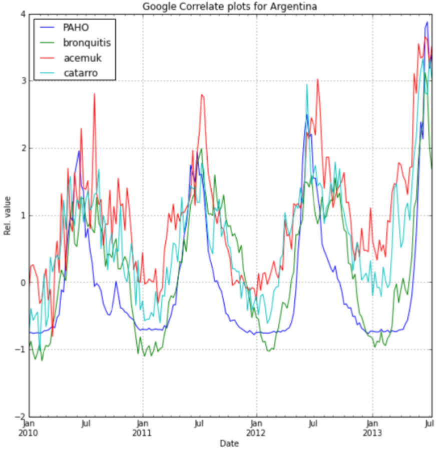
- Final filtering : 114 words

Finding Custom user keyword dictionary (contd..)

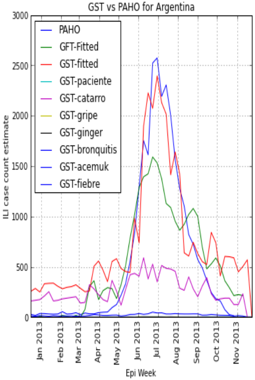


Symptomatic words: "bronquitis", "catarro", "tos seca" (whooping cough)

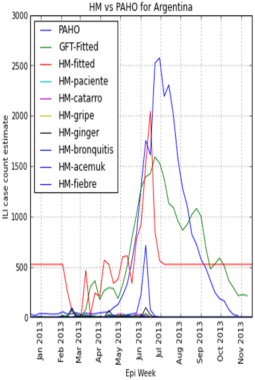
Medicinal words: "acemuk", "claritromicina" (clarithromycin)

Interesting words: ginger ("jengibre"), leave letter ("letra de deja")

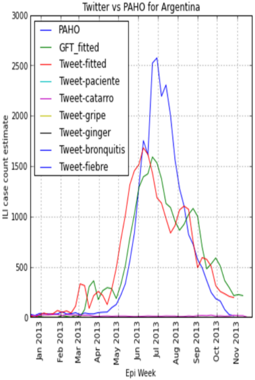
GFT vs other non-physical indicators using custom keyword set



Google Search Trends (GST)



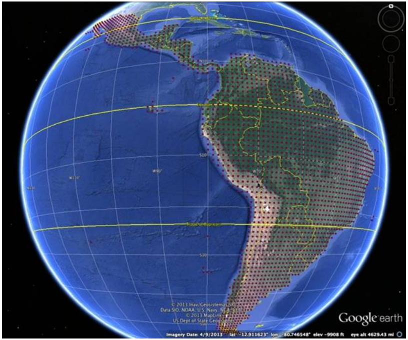
Healthmap



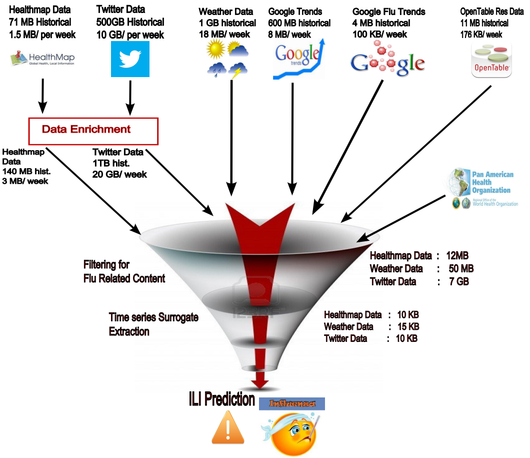
Twitter

Physical Indicators

- Meteorological data for every lat-long, worldwide, every 8 hours
- Humidity, Temperature, Rainfall
- Analyzing grid cells covering PAHO sites.



System framework once again!!



Preliminaries

- To find predictive model$f$

$$f : \mathcal{P}_t = f\left(\mathcal{P}, \mathcal{X}\right)$$

- Variable Setup

$$\begin{aligned} V_t &\equiv \langle P_{t-\beta-\alpha}, \mathcal{X}_{t-\beta-\alpha}, P_{t+1-\beta-\alpha}, \mathcal{X}_{t+1-\beta-\alpha}, \ldots, \\ &\quad P_{t-\alpha}, \mathcal{X}_{t-\alpha}\rangle \\ L_t &\equiv P_t \end{aligned}$$

- Parameters
  - α : the *lookahead window length*
  - β : the *lookback window length*

Matrix Factorization (MF)

- Can find latent factors in the dataset.

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- Fitting

$$b_*, F, U = \operatorname{argmin}\Big(\sum_{i=1}^{m-1} \left(\mathcal{M}_{i,n} - \widehat{\mathcal{M}}_{i,n}\right)^2 + \lambda_1\big(\sum_{j=1}^{n} b_j^2 + \sum_{i=1}^{m-1} ||U_i||^2 + \sum_{j=1}^{n} ||F_j||^2\big)\Big) \quad (1)$$

Nearest Neighbor model (NN)

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$$\widehat{P}_{T'} = \Big(\sum_{k \in \mathcal{N}(T')} \theta_k L_{k,T-\alpha}\Big) / \sum_{k=1}^{K} \theta_k \qquad (2)$$

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- $$\widehat{\mathcal{M}}_{i,j} = b_{i,j} + U_i^T F_j + F_j |\mathcal{N}(i)|^{-\frac{1}{2}} \sum_{k \in N(i)} (\mathcal{M}_{i,k} - b_{i,k}) x_k \quad (3)$$

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$$b_*, F, U, x_* = \mathrm{argmin}\left(\sum_{i=1}^{m-1} \left(\mathcal{M}_{i,n} - \widehat{\mathcal{M}}_{i,n}\right)^2 + \lambda_2\left(\sum_{j=1}^{n} b_j^2 + \sum_{i=1}^{m-1} ||U_i||^2 + \sum_{j=1}^{n} ||F_j||^2 + \sum_{k} ||x_k||^2\right)\right) \quad (4)$$

* Yehuda Koren. "Factorization meets the neighborhood: a multifaceted collaborative filtering model". In: *Proceedings of KDD '08.* 2008, pp. 426–434

Accuracy comparison

- Quality Metric

$$\mathcal{A} = \frac{4}{N_p} \sum_{t=t_s}^{t_e} \left(1 - \frac{|P_t - \hat{P}_t|}{max(P_t, \hat{P}_t, 10)} \right) \quad (5)$$

Accuracy comparison

Table 1: Comparing forecasting accuracy of models using individual sources. Scores in this and other tables are normalized to [0,4] so that 4 is the most accurate.

Model	Sources	AR	BO	CL	CR	CO	EC	GF	GT	HN	MX	NI	PA	PY	PE	SV	All
MF	$\mathcal{W}$	2.78	2.46	2.39	2.14	2.70	2.22	2.12	2.63	2.52	**2.73**	2.31	2.21	2.49	2.77	**2.61**	2.47
	$\mathcal{H}$	2.81	2.31	2.22	1.92	2.43	2.04	2.11	2.57	2.33	2.48	2.39	2.15	2.18	2.47	2.33	2.32
	$\mathcal{T}$	2.37	2.35	2.18	2.03	2.21	2.12	1.83	2.12	2.29	2.03	1.89	2.06	1.96	2.20	2.21	2.12
	$\mathcal{F}$	2.34	2.11	2.29	N/A	N/A	N/A	N/A	N/A	N/A	2.71	N/A	N/A	2.31	2.24	N/A	2.33
	$\mathcal{S}$	2.48	2.21	2.33	2.04	2.31	2.21	1.93	2.03	2.15	2.51	2.42	2.52	2.33	1.93	2.30	2.24
NN	$\mathcal{W}$	2.92	2.93	2.63	2.52	2.66	2.51	2.71	2.82	2.59	2.62	2.55	2.59	2.61	**2.80**	2.52	2.66
	$\mathcal{H}$	2.73	3.10	2.42	2.27	2.83	2.64	2.43	2.25	2.71	2.31	**2.61**	2.35	2.43	2.39	2.52	2.53
	$\mathcal{T}$	2.72	2.86	2.31	2.62	2.77	2.52	2.71	2.66	2.51	2.44	2.13	2.01	1.77	2.51	2.20	2.45
	$\mathcal{F}$	2.11	2.21	2.33	N/A	N/A	N/A	N/A	N/A	N/A	2.19	N/A	N/A	2.41	2.32	N/A	2.26
	$\mathcal{S}$	2.51	2.31	2.41	1.81	2.52	2.41	2.12	2.29	2.51	2.13	**2.61**	2.14	2.51	1.87	2.12	2.28
MFN	$\mathcal{W}$	**2.99**	3.01	**2.88**	2.53	2.78	**2.81**	2.77	**2.83**	2.61	2.70	2.56	**2.66**	**2.82**	2.79	2.51	**2.75**
	$\mathcal{H}$	2.81	**3.13**	2.63	2.58	**2.91**	2.77	2.57	2.63	**2.73**	2.50	**2.61**	2.54	2.51	2.69	**2.61**	2.68
	$\mathcal{T}$	2.74	3.03	2.51	**2.64**	2.83	2.51	**2.81**	2.71	2.60	2.48	2.13	2.55	2.19	2.57	2.31	2.57
	$\mathcal{F}$	2.33	2.41	2.34	N/A	N/A	N/A	N/A	N/A	N/A	2.69	N/A	N/A	2.54	2.48	N/A	2.46
	$\mathcal{S}$	2.61	2.44	2.55	2.22	2.61	2.52	2.71	2.31	2.62	2.48	**2.61**	2.31	2.53	2.23	2.13	2.46

- On average, MFN has better performance over MF and NN
- In Mexico, MF has the best accuracy - possibly because the 2013 ILI season in Mexico was late by a few weeks than in usual.

Model level fusion

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$$ {}_{C}\widehat{\mathcal{M}}_{i,j} = \mu_i + {}_{C}b_j + {}_{C}U_i^T \, {}_{C}F_j \\ + {}_{C}F_j |{}_{C}\mathcal{N}(i)|^{-\frac{1}{2}} \sum_{k \in {}_{C}N(i)} ({}_{C}\mathcal{M}_{i,k} - \mu_i + {}_{C}b_k) {}_{C}x_k \quad (7) $$

Data level fusion

- Feature vector is a tuple over all data set features.

$$\mathcal{X}_t = \langle \mathcal{T}_t, \mathcal{W}_t \rangle$$

- Use MFN to fit the value

Accuracy comparison

Table 2: Comparison of prediction accuracy while combining all data sources and using MFN regression.

Fusion Level	AR	BO	CL	CR	CO	EC	GF	GT	HN	MX	NI	PA	PY	PE	SV	All
Model	**3.12**	**3.22**	3.03	**2.88**	**2.98**	**3.13**	2.87	**2.99**	**2.87**	**3.00**	**2.77**	**2.82**	2.81	**2.92**	2.87	**2.95**
Data	3.01	2.97	**3.13**	2.87	2.86	3.04	**2.91**	2.88	2.72	2.89	2.70	2.60	**2.88**	2.81	**2.92**	2.88

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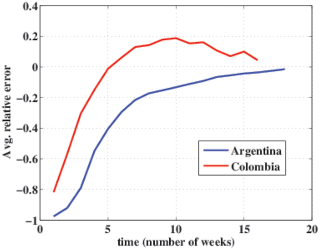
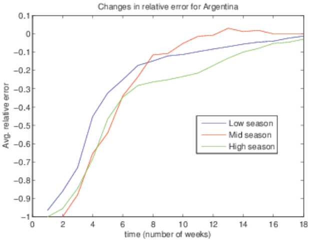
Data	3.01	2.97	**3.13**	2.87	2.86	3.04	**2.91**	2.88	2.72	2.89	2.70	2.60	**2.88**	2.81	**2.92**	2.88

- On average, model level fusion produces better accuracy than data level fusion.
- Interesting deviations like Chile and El Salvador indicates that a possible strategy could be a mix of data level and model fusion - however complexity of training will increase manifold.

Uncertainty in official estimates

- Can take up to several months to stabilize.





- Average relative error of PAHO count values with respect to stable values. (a) Comparison between Argentina and Colombia (b) Comparison between different seasons for Argentina.

Correcting uncertainty

- Recognize high, low and mid-season months for countries.
- Variable setup

$$\mathcal{P}_A{}^S = \left\{(1, P_i^{(1)}, \dot{P}_i, N_i^{(1)}), ..., (m, P_i^{(m)}, \dot{P}_i, N_i^{(m)}), ...\right\}$$

- Correction Model

$$\hat{\dot{P}}_i^{(m)} = a_0 + a_1 m + a_2 P_i^{(m)} + a_3 N_i^{(m)} \tag{8}$$

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Table 3: Comparison of prediction accuracy while using model level fusion on MFN regressors and employing PAHO stabilization.

Correction Method	AR	BO	CL	CR	CO	EC	GF	GT	HN	MX	NI	PA	PY	PE	SV	All
None	3.12	3.22	3.03	2.88	**2.98**	3.13	2.87	2.99	2.87	3.00	2.77	2.82	2.81	**2.92**	2.87	2.95
Weeks Ahead	3.15	**3.24**	3.04	2.87	2.97	3.17	2.87	2.99	2.88	3.05	2.77	2.91	3.02	2.91	**2.88**	2.98
Num. samples	3.20	**3.24**	3.03	2.88	2.96	3.12	2.87	**3.01**	**2.89**	3.12	**2.78**	2.92	3.04	2.91	2.87	2.99
Combined	**3.21**	**3.24**	**3.05**	**2.89**	2.96	**3.19**	**2.88**	3.00	**2.89**	**3.13**	2.77	**2.93**	**3.08**	**2.92**	**2.88**	**3.00**

Investigating importance of each source : Ablation Test

Table 4: Discovering importance of sources in Model level fusion on MFN regressors by ablating one source at a time.

Sources	AR	BO	CL	CR	CO	EC	GF	GT	HN	MX	NI	PA	PY	PE	SV	All
All	**3.21**	**3.24**	**3.05**	**2.89**	**2.96**	**3.19**	2.87	**3.00**	**2.89**	**3.13**	**2.77**	**2.93**	**3.08**	**2.92**	**2.88**	**3.00**
w/o $\mathcal{W}$	2.91	2.99	2.77	2.71	2.61	2.59	2.66	2.69	2.49	2.78	2.62	2.87	2.60	2.43	2.67	2.69
w/o $\mathcal{H}$	3.04	2.85	2.89	2.56	2.81	2.77	2.61	2.75	2.75	2.82	2.57	2.75	2.51	2.87	2.71	2.75
w/o $\mathcal{T}$	2.92	3.14	2.95	2.61	2.72	2.81	2.88	2.79	2.61	2.93	2.74	2.63	2.79	2.74	2.81	2.80
w/o $\mathcal{S}$	3.19	3.11	2.92	2.64	2.69	2.70	**2.89**	2.88	2.78	3.07	2.75	2.91	2.80	2.71	2.86	2.86
w/o $\mathcal{F}$	3.20	3.12	2.88	**2.89**	**2.96**	**3.19**	2.87	**3.00**	2.83	3.02	**2.77**	**2.93**	2.98	2.88	**2.88**	2.96

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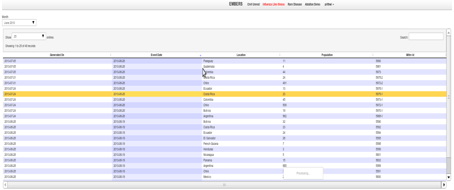
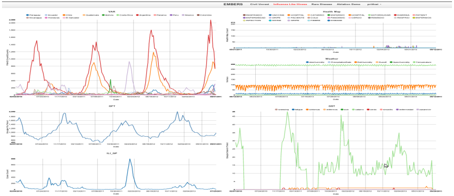
w/o $\mathcal{W}$	2.91	2.99	2.77	2.71	2.61	2.59	2.66	2.69	2.49	2.78	2.62	2.87	2.60	2.43	2.67	2.69
w/o $\mathcal{H}$	3.04	2.85	2.89	2.56	2.81	2.77	2.61	2.75	2.75	2.82	2.57	2.75	2.51	2.87	2.71	2.75
w/o $\mathcal{T}$	2.92	3.14	2.95	2.61	2.72	2.81	2.88	2.79	2.61	2.93	2.74	2.63	2.79	2.74	2.81	2.80
w/o $\mathcal{S}$	3.19	3.11	2.92	2.64	2.69	2.70	**2.89**	2.88	2.78	3.07	2.75	2.91	2.80	2.71	2.86	2.86
w/o $\mathcal{F}$	3.20	3.12	2.88	**2.89**	**2.96**	**3.19**	2.87	**3.00**	2.83	3.02	**2.77**	**2.93**	2.98	2.88	**2.88**	2.96

- Greater drop in accuracy $\Longrightarrow$ Source more important
- Physical indicators are in general more important
- Still there is value in supplementing physical indicators with non-physical indicators.

Final look at real time predictions

- Weekly predictions sent out for 15 Latin American countries
- Predictions publicly available at `http://embers.cs.vt.edu/embers/alerts/visualizer_isi`





Conclusion:
How to extend to other sources

- Data about number of unreserved tables at restaurants in Mexico

Table 5: ILI case count prediction accuracy for Mexico using OpenTable data as a single source, and by combining it with all other sources using model level fusion on uncorrected ILI case count data.

Method	Lunch	Dinner	Lunch & Dinner
MF	1.92	2.23	2.31
NN	1.99	1.83	2.11
MFN	2.11	2.31	2.44
Model Fusion	**2.96**	**2.87**	**2.99**

Summary

- MFN performs better than MF, NN on average over individual sources for predicting ILI case counts.
- In average there is a small advantage in combining models over different sources than to combine data.
- Employing information about number of samples used and how far from the actual date the estimate is being updated by the reporting agency, we have been able to improve our overall accuracy by a quality score of 0.05.
- Generally physical indicators offer more advantage over non-physical indicators. However for some situations Healthmap and Twitter feed have been found to outperform physical indicators.
- Experiments with Opentable reservation data shows that there is some perceptible signal embedded w.r.t to ILI case counts.

Future Work

- Reconcile these phenomenological models with true epidemiological models.
- Explore inter-country characteristics of ILI profiles.

Acknowledgements

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Thanks!

Thanks!

Any questions?

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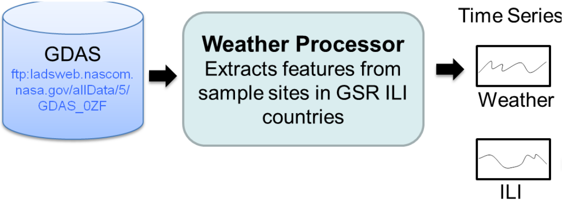
Appendix: Physical Indicators Collection Framework



Appendix: Accuracy of different methods for different countries

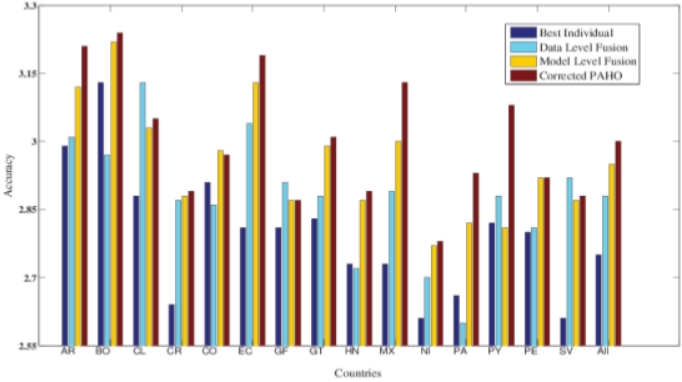


Figure 4: Accuracy of different methods for each country.