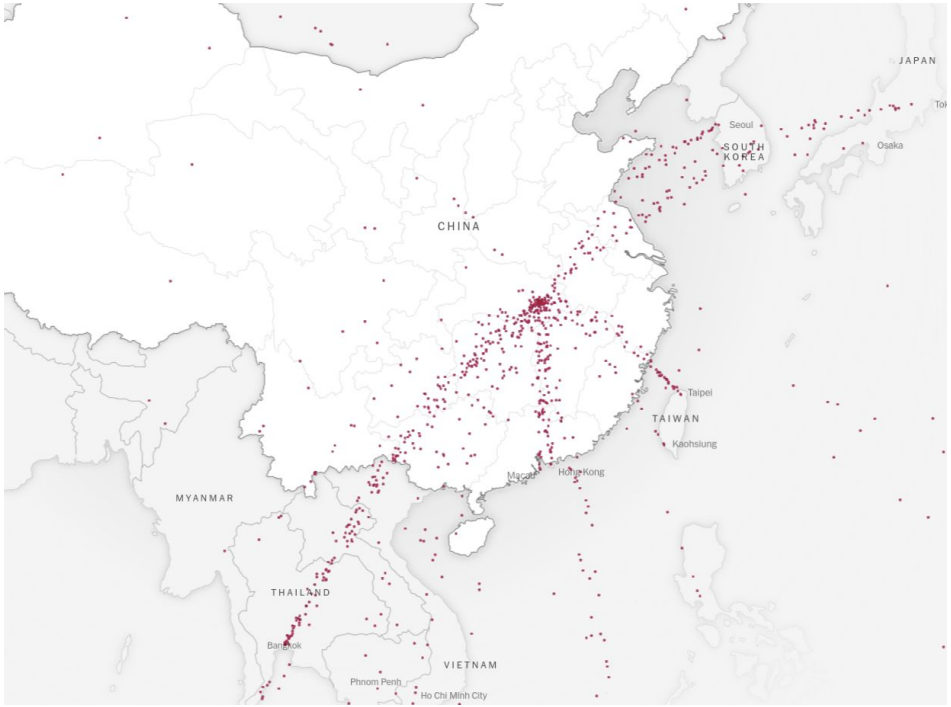
Corona-Vis:
Covid-19 around the world

Expansion of COVID-19

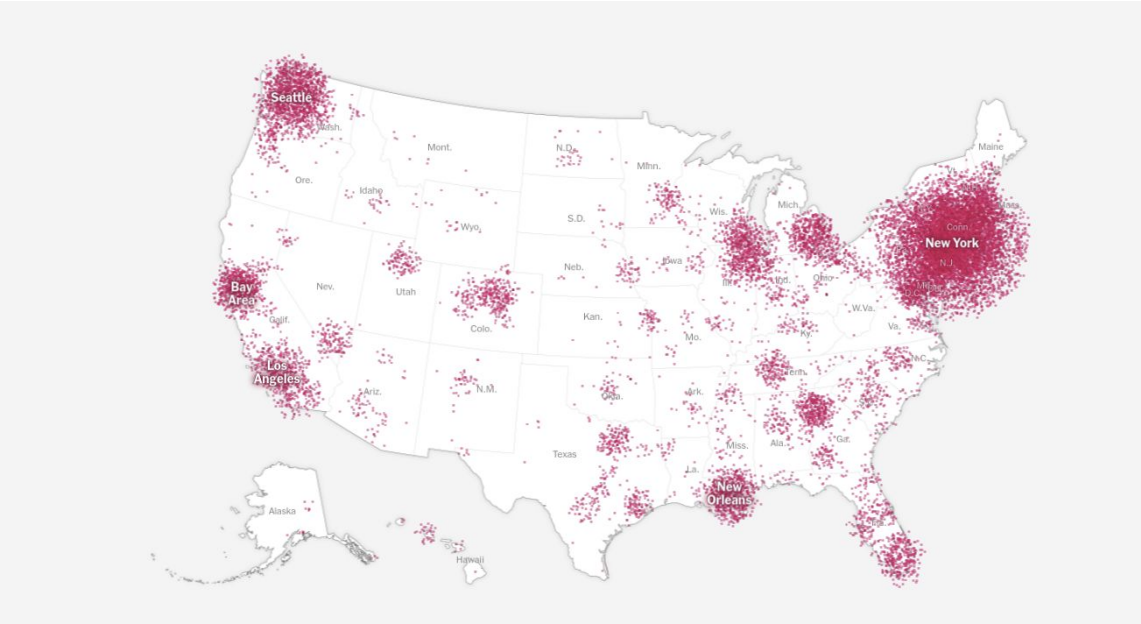
-



New York Times, covid-19 China.

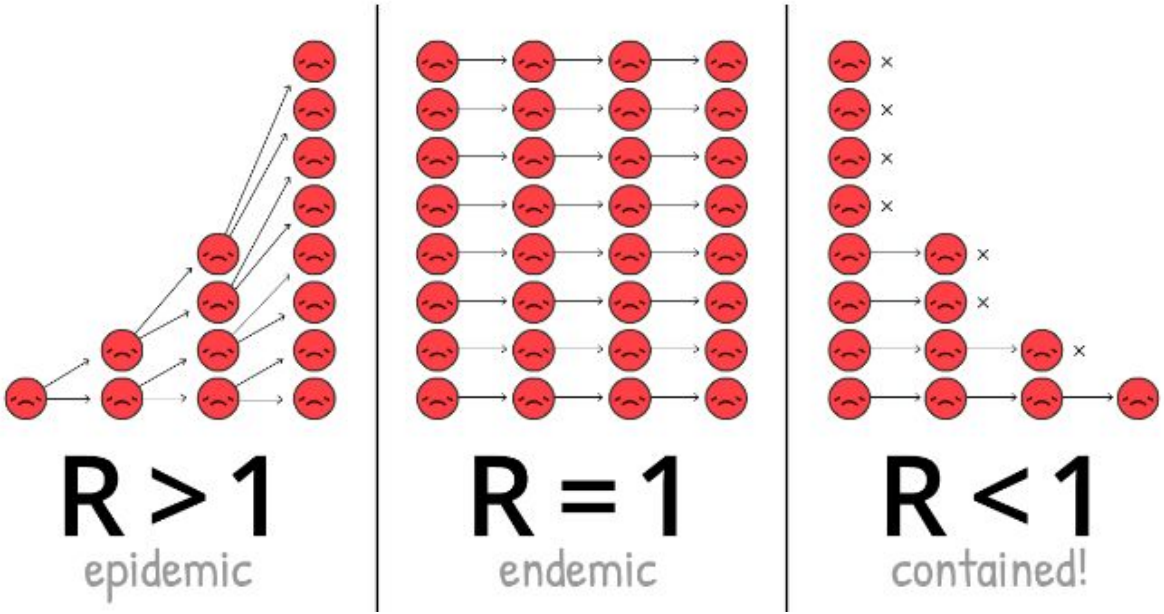
Expansion of COVID-19

-



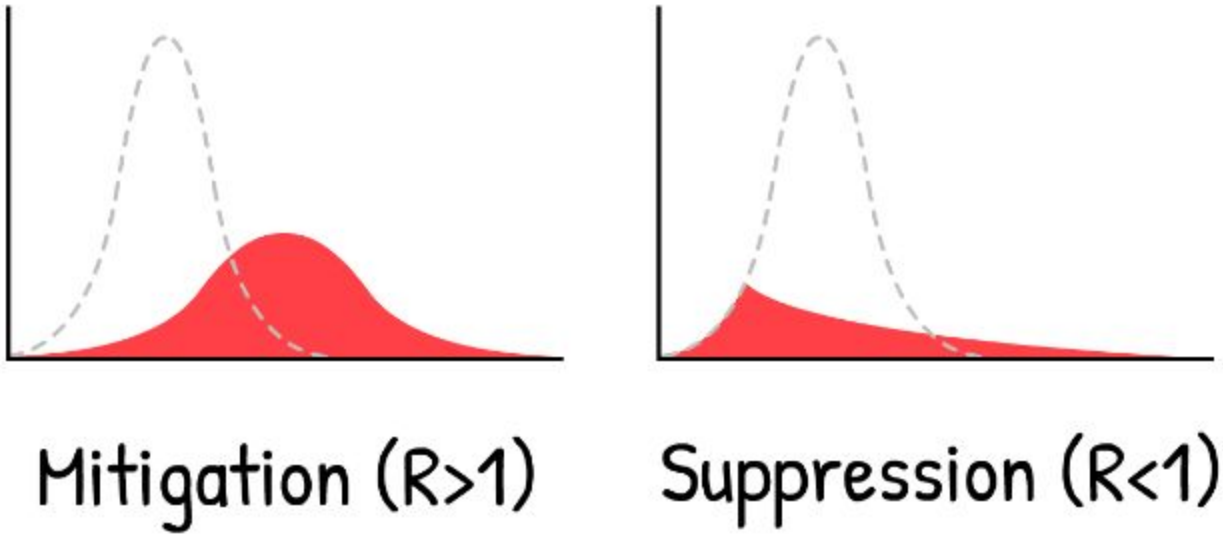
New York Times, covid-19 EEUU.

Prediction basic reproductive ratio (R) through time



Source: https://ncase.me/covid-19/

Prediction basic reproductive ratio (R) through time



Source: https://ncase.me/covid-19/

Estimation: Bettencourt & Ribeiro 2008 - SIR model

Estimate real-time Rt using a Bayesian approach with Gaussian noise.

$$\frac{dS}{dt} = -\beta \frac{S}{N} I \quad \frac{dI}{dt} = \beta \frac{S}{N} I - \gamma I,$$

Where I is the average number of infectious (rate), S is average number of susceptibles at time t (k)

So we have the bayes rule having seen new cases, we believe the distribution Rt of is equal to:

$$P(R_t|k) = \frac{P(k|R_t) \cdot P(R_t)}{P(k)}$$

- The **likelihood** of seeing k new cases given Rt times ...
- The **prior** beliefs of the value of without the data ...
- divided by the probability of seeing this many cases in general

Source: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0002185

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So, to estimate today's prior P(Rt) we use yesterday's prior P(Rt-1) assuming that Rt is a gaussian distribution with center in Rt-1.

$$P(R_t|R_{t-1}) = N(R_{t-1}, \sigma)$$

$$P(R_1|k_1) \propto P(R_1) \cdot \mathscr{L}(R_1|k_1)$$

On day two:

$$P(R_2|k_1, k_2) \propto P(R_2) \cdot \mathcal{L}(R_2|k_2) = \sum_{R_1} P(R_1|k_1) \cdot P(R_2|R_1) \cdot \mathcal{L}(R_2|k_2)$$

Source: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0002185
https://en.wikipedia.org/wiki/Compartmental_models_in_epidemiology

Estimation: Bettencourt & Ribeiro 2008 - SIR model

Each new arrival will modeled by continuous distribution poisson like:

$$P(k|\lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$$

Given an average arrival rate of λ new cases per day, the probability of seeing k new cases

Finding relationship between Rt and λ , so We have $P(\lambda_t|k_t)$ which is parameterized by λ but we were looking for $P(k_t|R_t)$.

So, calculating the derivation we have $\lambda = k_{t-1}e^{\gamma(R_t-1)}$, where γ is the reciprocal of the serial interval (with value of 7 for Covid-19*).

Source: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0002185

* https://wwwnc.cdc.gov/eid/article/26/7/20-0282_article

Estimation: Bettencourt & Ribeiro 2008 - SIR model

Since we know every new case count on the previous day, we can now reformulate the likelihood function as a Poisson parameterized by fixing k and varying Rt, we have:

$$\lambda = k_{t-1} e^{\gamma(R_t - 1)} \qquad P(k|R_t) = \frac{\lambda^k e^{-\lambda}}{k!}$$

So we calculate the likelihood to get the best σ, tha maximizes k: $P(k|\sigma)$, that is maximizes P(k).

$$P(k) = P(k_0, k_1, \ldots, k_t) = P(k_0)P(k_1)\ldots P(k_t)$$

Using Bayes to calculate P(kt), we have:

$$P(R_t|k_t) = \frac{P(k_t|R_t)P(R_t)}{P(k_t)} \qquad P(k_t,\ R_t) = P(k_t|R_t)P(R_t) \qquad P(k_t) = \sum_{R_t} P(k_t|R_t)P(R_t)$$

Source: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0002185

Estimation: Bettencourt & Ribeiro 2008 - SIR model

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Likelihood:

$$L(P(k)) = \prod P(k_0) P(k_1) \dots P(k_t)$$

Maximizes the likelihood is the same as minimizing "negative log likelihood":

$$log(L(P(k))) = \sum_{i=0}^{t} log(P(k_i))$$

Source: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0002185

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We obtain the best σ, derivating the log of the likelihood:

$$\sigma = \sqrt{\frac{1}{n} \sum (k_i - \mu)}$$

Where μ:

$$\mu = \frac{1}{n} \sum k_i$$

Source: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0002185

Confidence Interval:

$$P(Z \leq z) = 1 - \alpha/2$$

$$P(Z \leq z) = 0.9$$

$$\phi(z) = 0.9$$

$$P(-z \leq \frac{X-\mu}{\sigma/\sqrt{n}} \leq z) = 0.9$$

Source: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0002185

Data Source

- Plataforma Nacional de Datos Abiertos, Minsa, Peru.
- Data positivo por COVID-19 - [Ministerio de Salud]

Open data from “Ministerio de Salud”

Source: https://www.datosabiertos.gob.pe/dataset/casos-positivos-por-covid-19-ministerio-de-salud-minsa

Data Source

- Structure
  - UUID
  - Departamento
  - Provincia
  - Distrito
  - Método
  - Edad
  - Sexo
  - Fecha Resultado

	UUID	DEPARTAMENTO	PROVINCIA	DISTRITO	METODODX	EDAD	SEXO	FECHA_RESULTADO
0	7320cabdc1aaca6c59014cae76a134e6	LIMA	LIMA	LIMA	PCR	32.0	MASCULINO	23/05/2020
1	e81602051997ace8340bb8c18fe24c65	LIMA	LIMA	MIRAFLORES	PCR	63.0	MASCULINO	23/05/2020
2	cecdbf10074dbc011ae05b3cbd320a6f	LIMA	LIMA	LA VICTORIA	PCR	45.0	MASCULINO	23/05/2020
3	71ecb6bccb248b0bb2ac72ed51b5e979	LIMA	LIMA	CHORRILLOS	PCR	37.0	MASCULINO	23/05/2020
4	566af4276cbe9359abe93f9aa86396c3	LIMA	LIMA	LIMA	PCR	25.0	MASCULINO	23/05/2020
...	...	...	...	...	...	...	...	...
123974	2549a57f71a380ee34b55354268e6c86	UCAYALI	CORONEL PORTILLO	CALLERIA	PR	30.0	FEMENINO	11/05/2020
123975	f3b32bee298af92986485f48867e163c	UCAYALI	CORONEL PORTILLO	CALLERIA	PR	46.0	MASCULINO	9/05/2020
123976	fbbaf38dee89edd2257c0c6e8f5b9123	UCAYALI	CORONEL PORTILLO	MANANTAY	PR	65.0	MASCULINO	23/05/2020
123977	be8057931a6e88bd760a101c0d2c6151	UCAYALI	CORONEL PORTILLO	CALLERIA	PR	37.0	MASCULINO	22/05/2020
123978	cdd2d9cb9abeaf9f12f82265918ededd	UCAYALI	CORONEL PORTILLO	YARINACOCHA	PR	25.0	MASCULINO	9/05/2020

Open data from “Ministerio de Salud”

Source: https://www.datosabiertos.gob.pe/dataset/casos-positivos-por-covid-19-ministerio-de-salud-minsa

Data Source

Errors:

- 11443 / 123979 wrong values.
- 0 or 1 value per district.

	UUID	DEPARTAMENTO	PROVINCIA	DISTRITO	METODODX	EDAD	SEXO	FECHA_RESULTADO
0	7320cabdc1aaca6c59014cae76a134e6	LIMA	LIMA	LIMA	PCR	32.0	MASCULINO	23/05/2020
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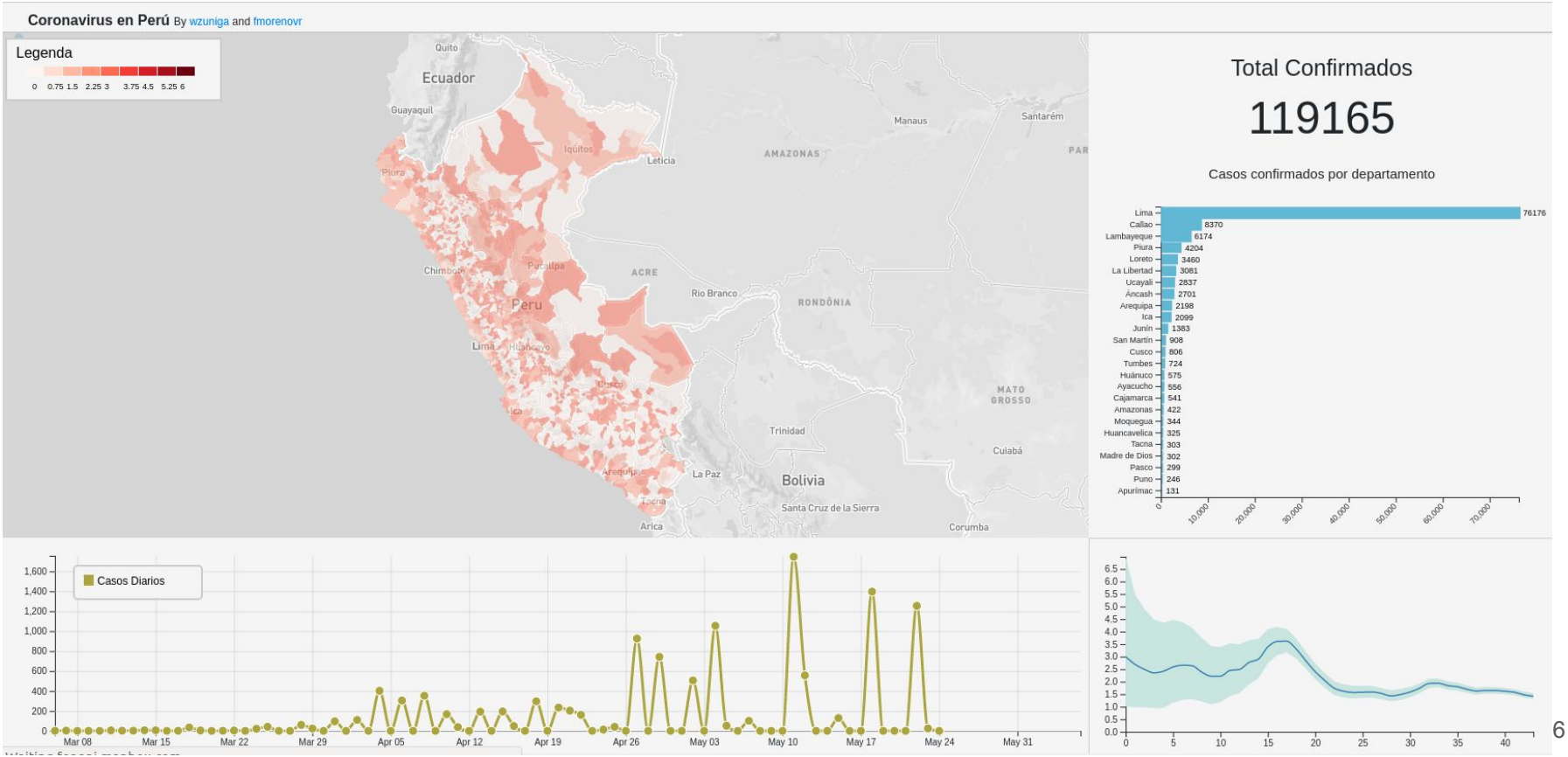
3	71ecb6bccb248b0bb2ac72ed51b5e979	LIMA	LIMA	CHORRILLOS	PCR	37.0	MASCULINO	23/05/2020
4	566af4276cbe9359abe93f9aa86396c3	LIMA	LIMA	LIMA	PCR	25.0	MASCULINO	23/05/2020
...	...	...	...	...	...	...	...	...
123974	2549a57f71a380ee34b55354268e6c86	UCAYALI	CORONEL PORTILLO	CALLERIA	PR	30.0	FEMENINO	11/05/2020
123975	f3b32bee298af92986485f48867e163c	UCAYALI	CORONEL PORTILLO	CALLERIA	PR	46.0	MASCULINO	9/05/2020
123976	fbbaf38dee89edd2257c0c6e8f5b9123	UCAYALI	CORONEL PORTILLO	MANANTAY	PR	65.0	MASCULINO	23/05/2020
123977	be8057931a6e88bd760a101c0d2c6151	UCAYALI	CORONEL PORTILLO	CALLERIA	PR	37.0	MASCULINO	22/05/2020
123978	cdd2d9cb9abeaf9f12f82265918ededd	UCAYALI	CORONEL PORTILLO	YARINACOCHA	PR	25.0	MASCULINO	9/05/2020

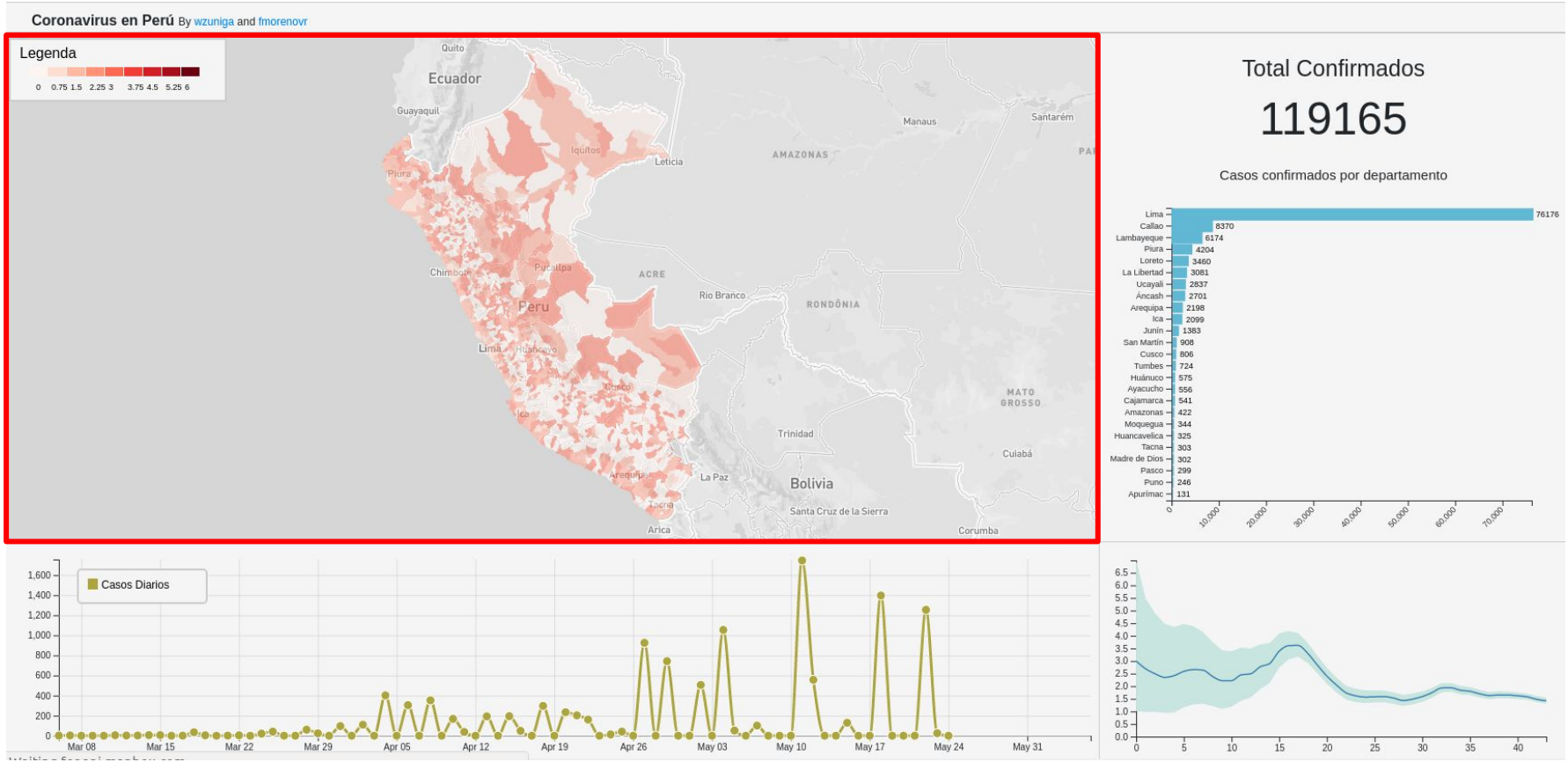
Open data from “Ministerio de Salud”

Source: https://www.datosabiertos.gob.pe/dataset/casos-positivos-por-covid-19-ministerio-de-salud-minsa

CoronaVis 2.0



Case Example: Perú - Deparments



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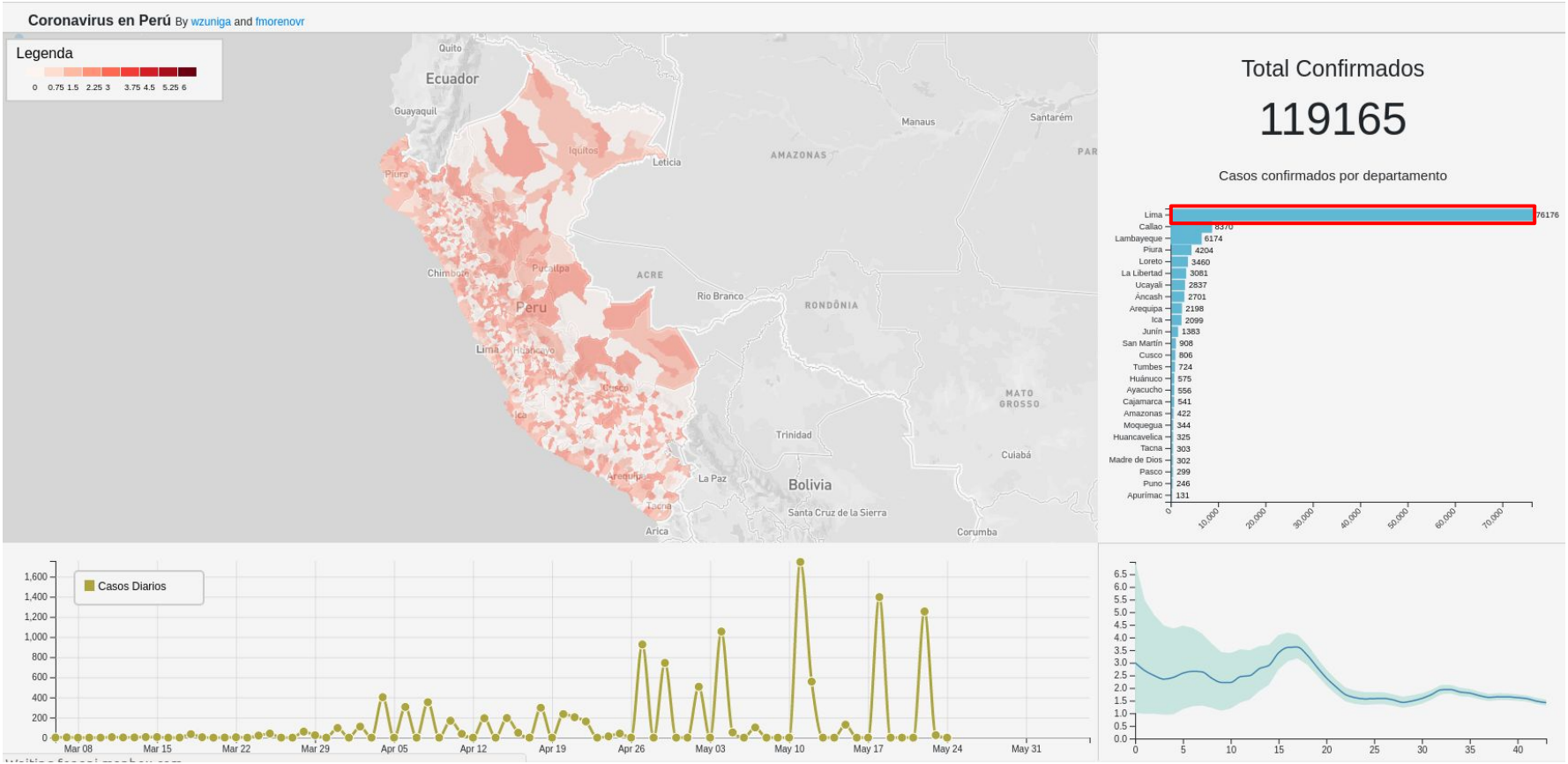
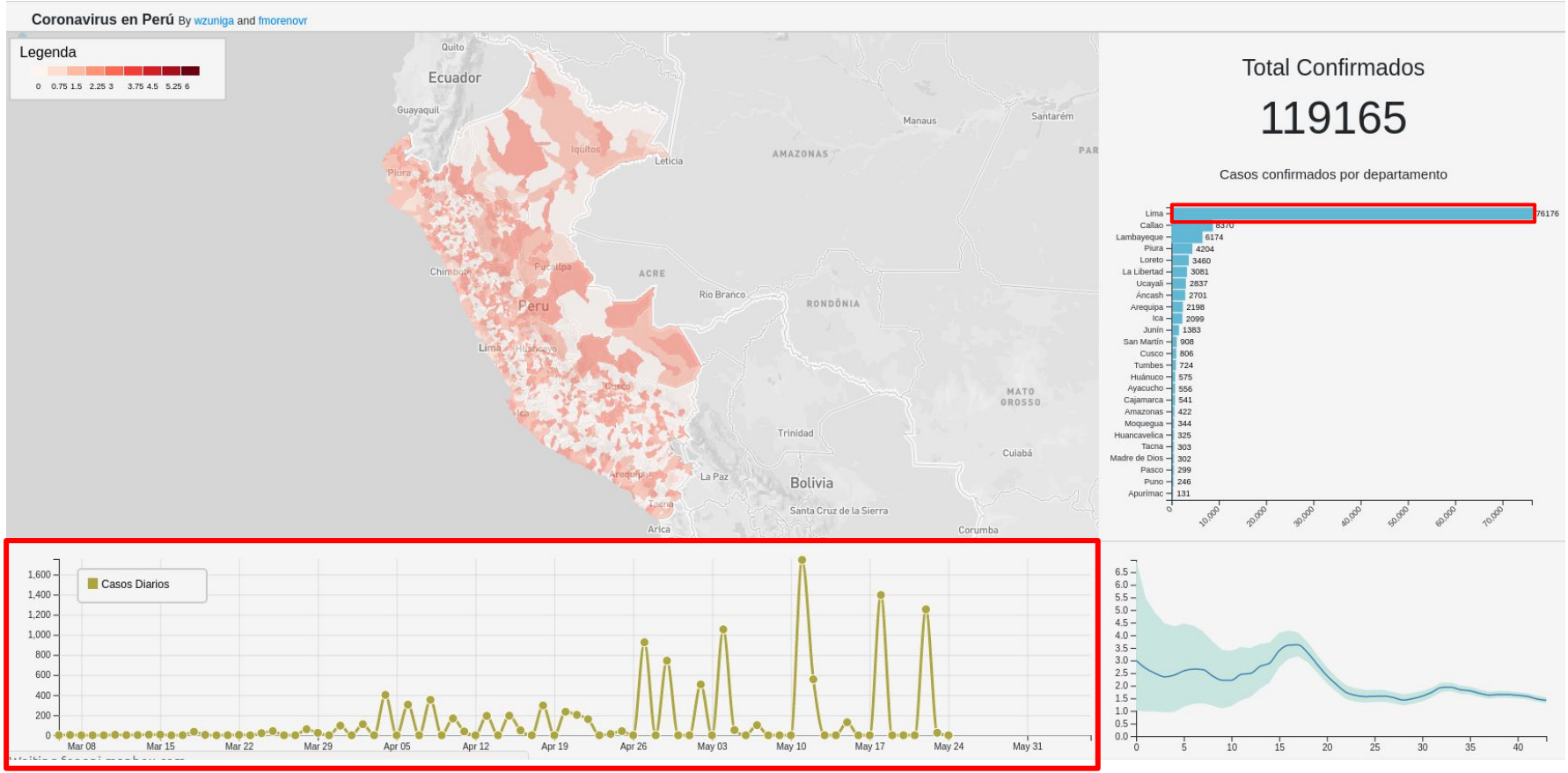
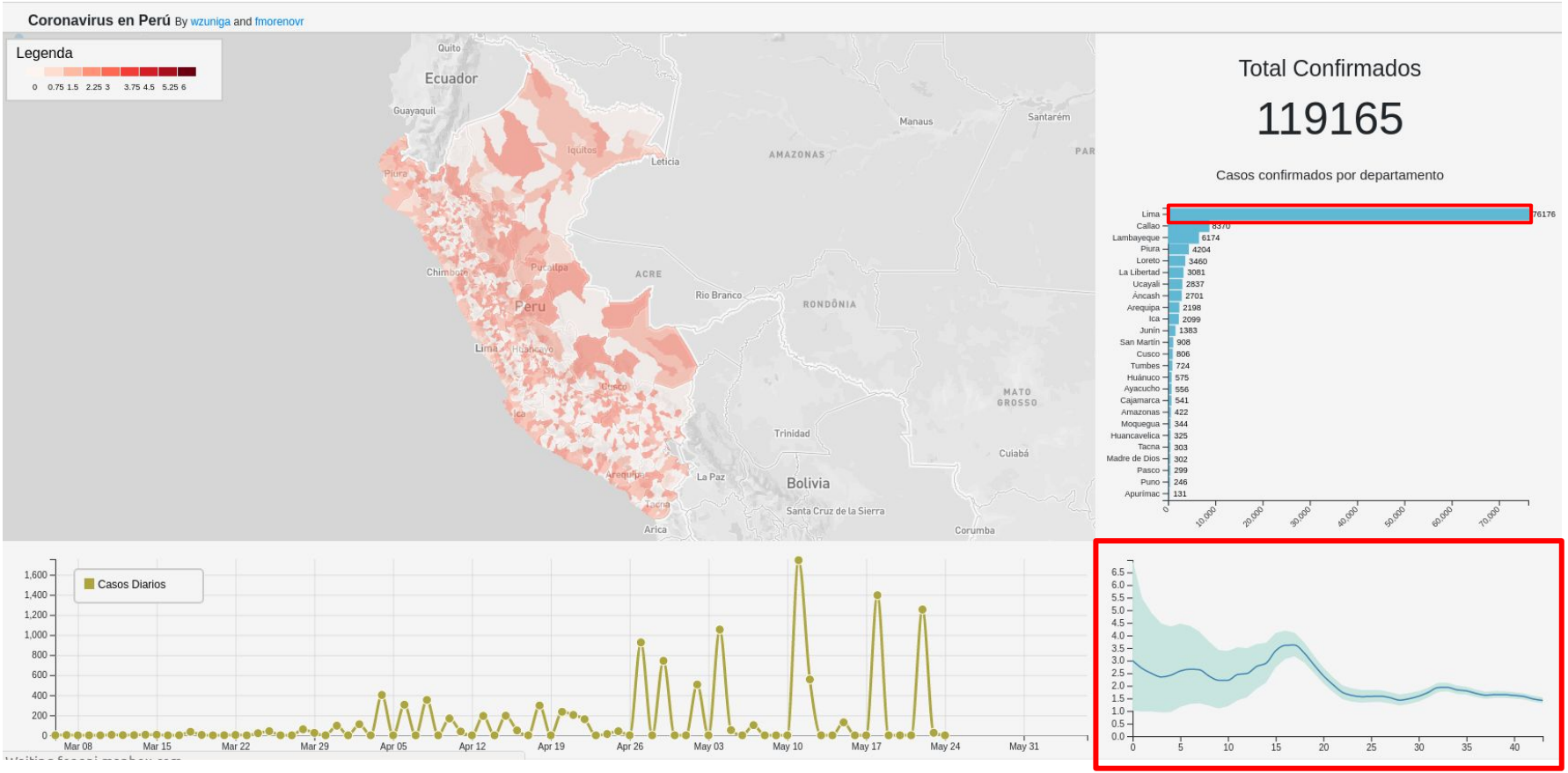


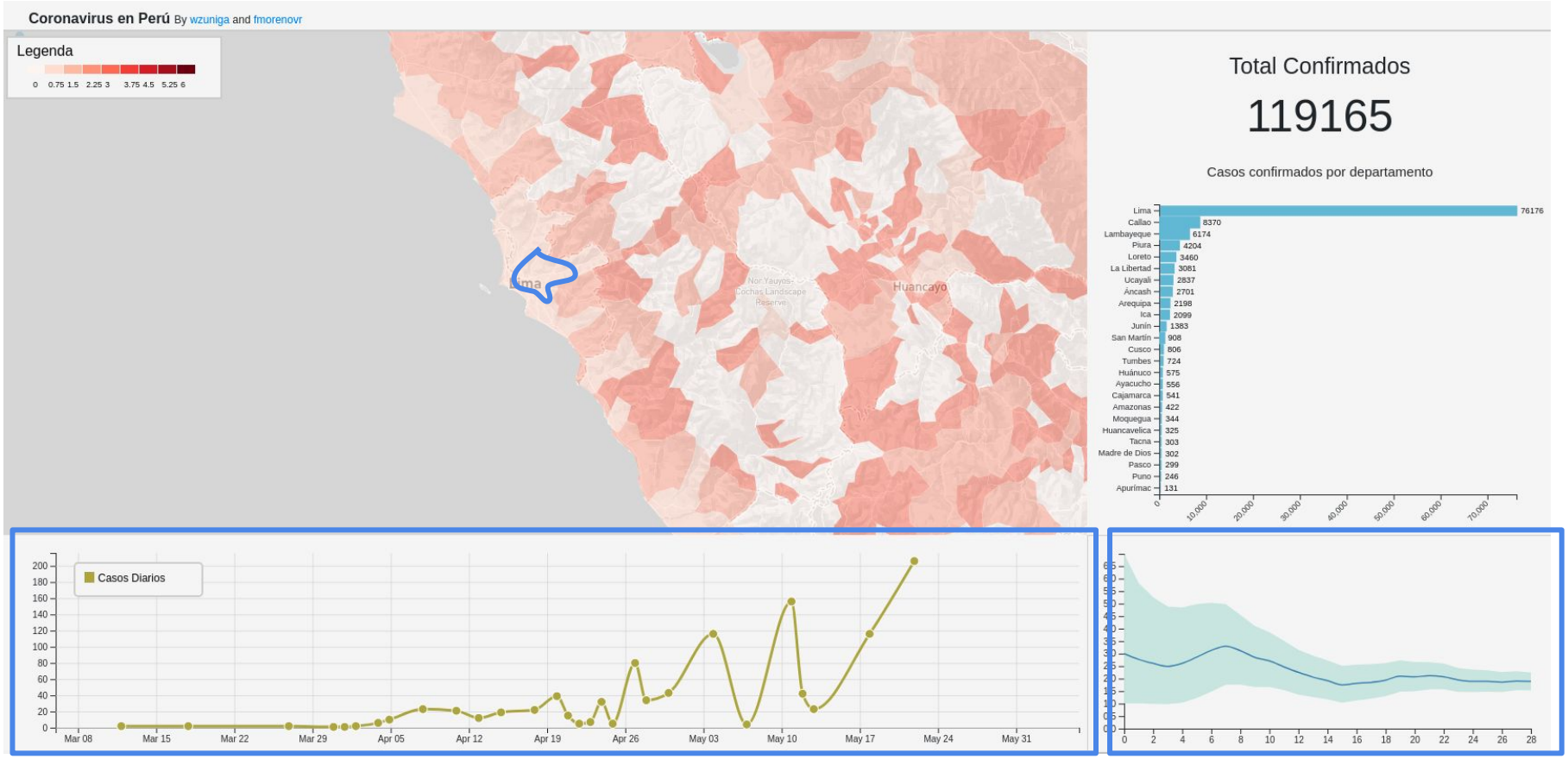
Case Example: Perú - Deparments



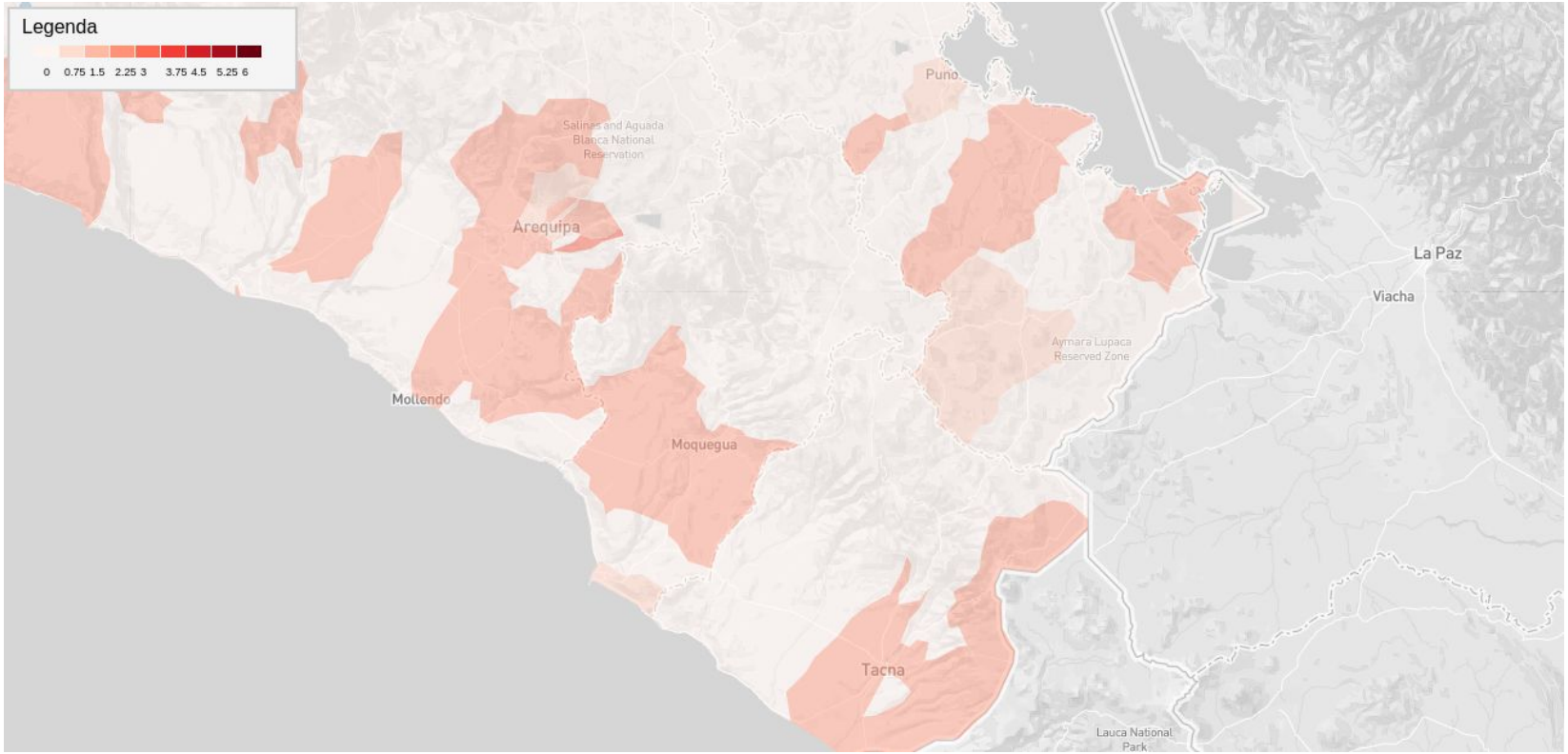
Case Example: Perú - Deparmento



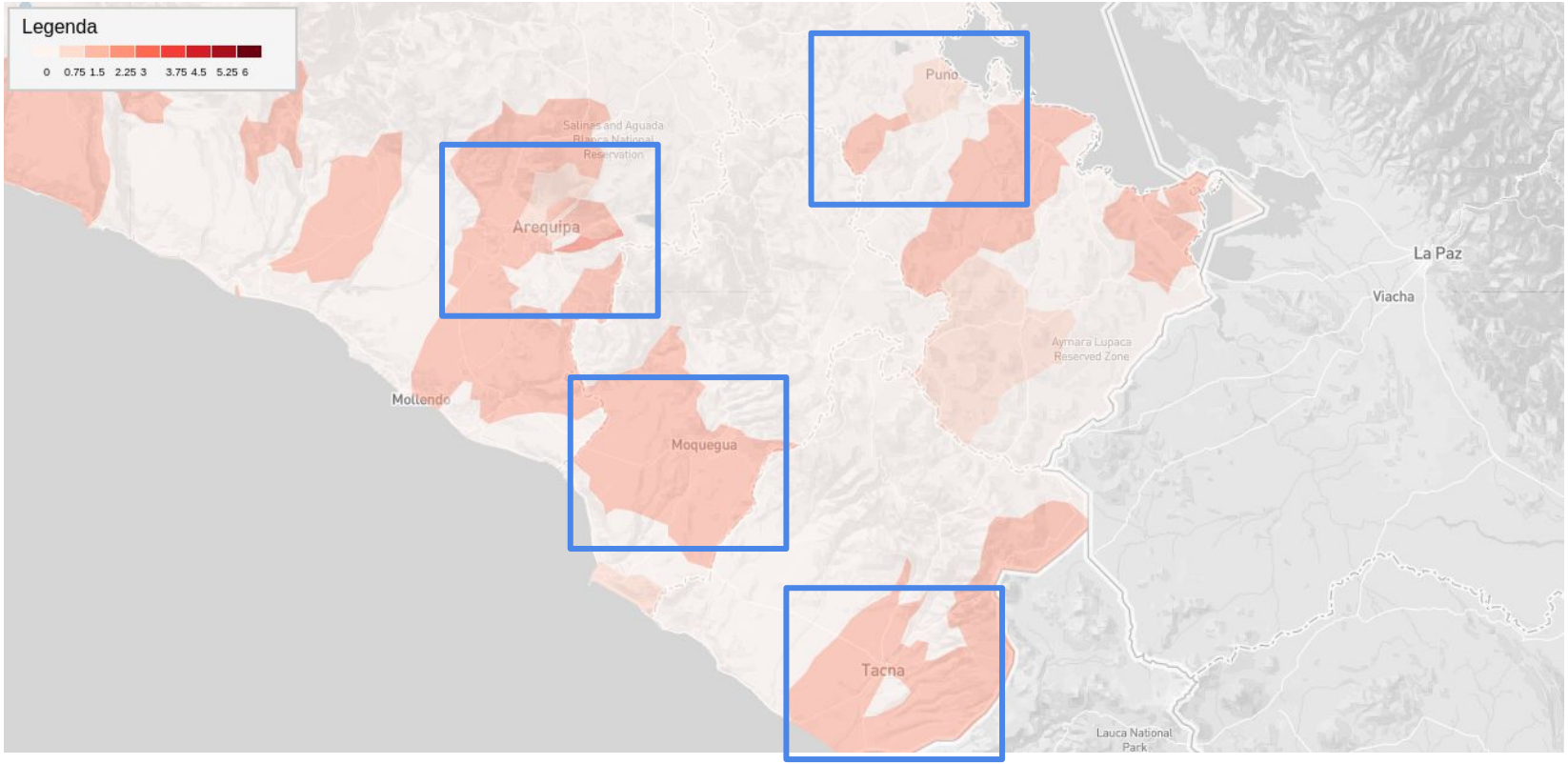
Case Example: Perú - Distritos



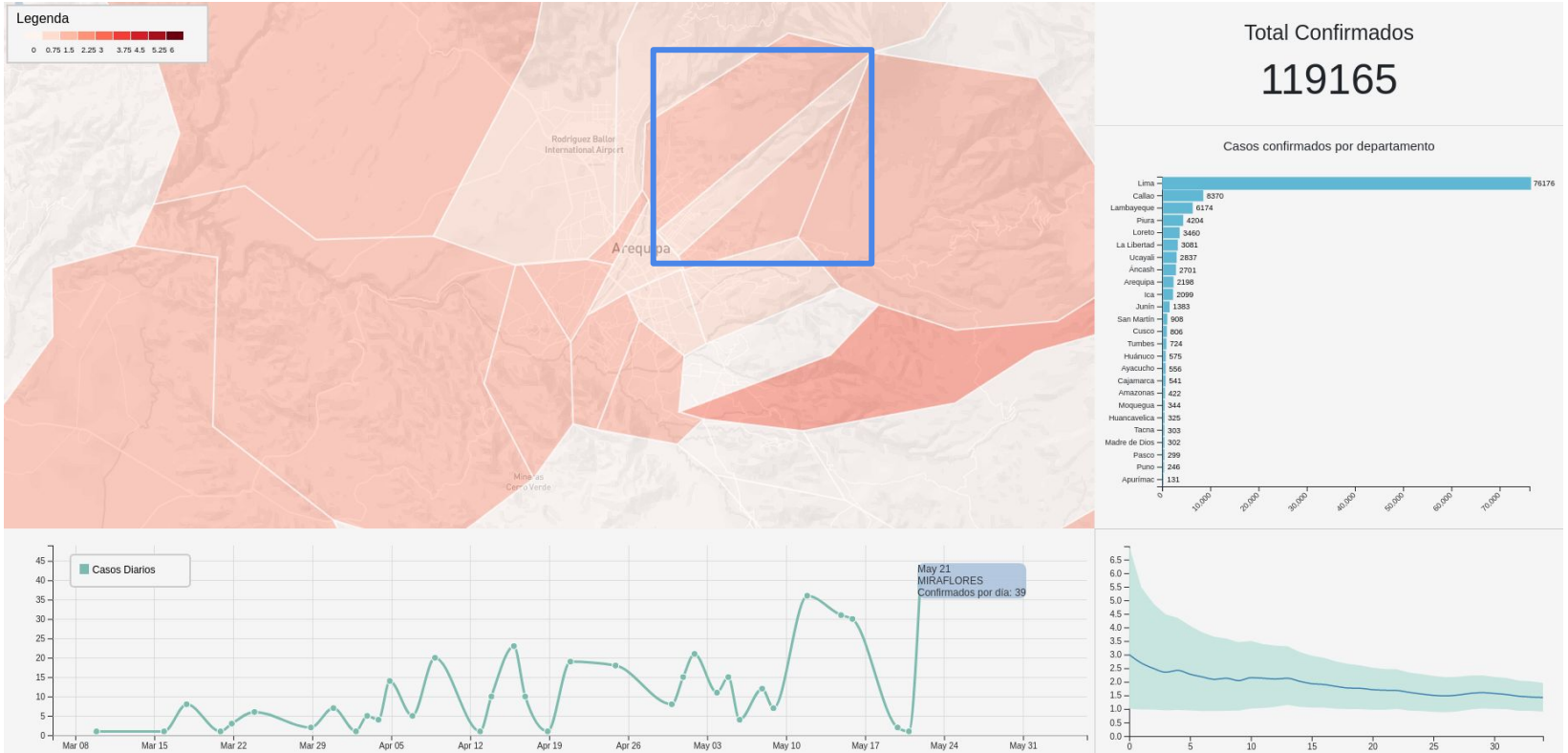
Case Example: Perú - Districts



Case Example: Perú - Districts

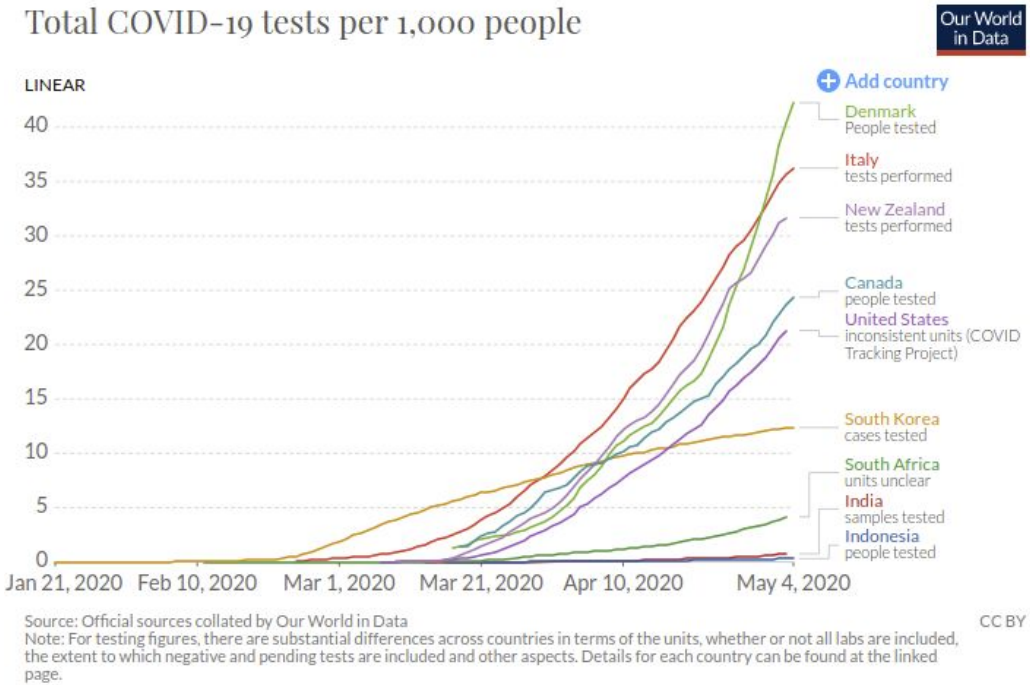


Case Example: Perú - Districts



Thank you!

Visual Analysis



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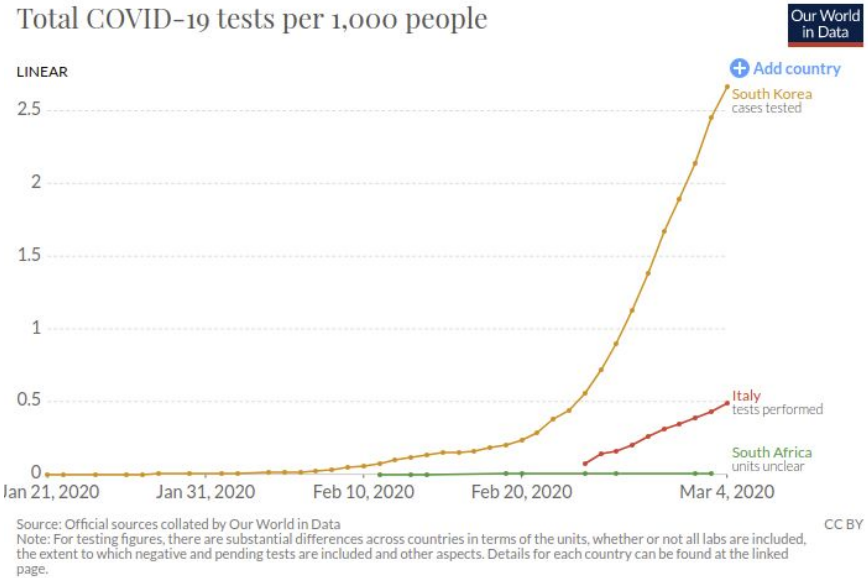

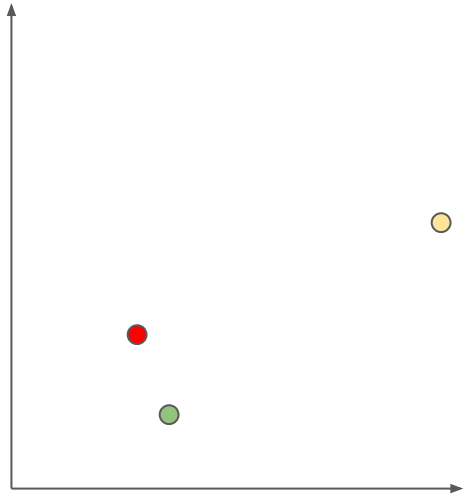

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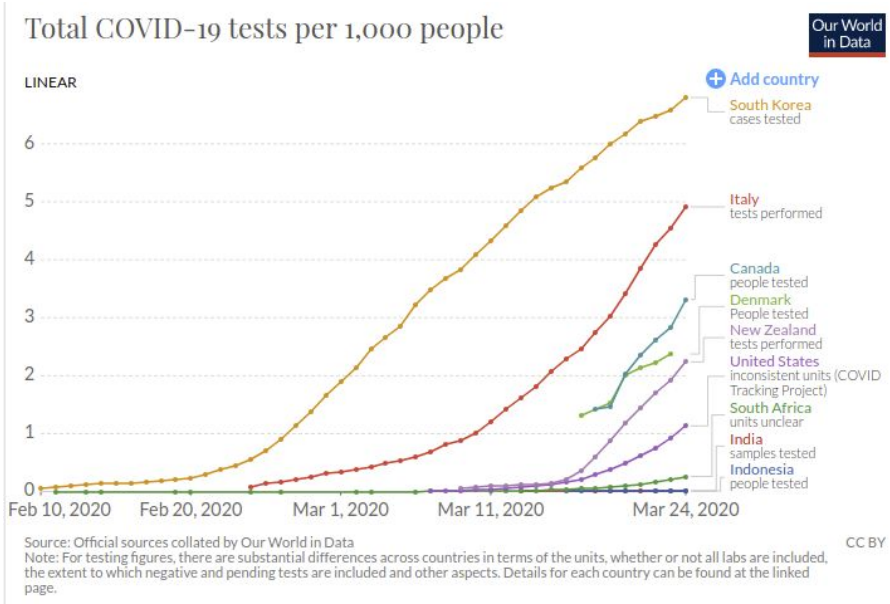

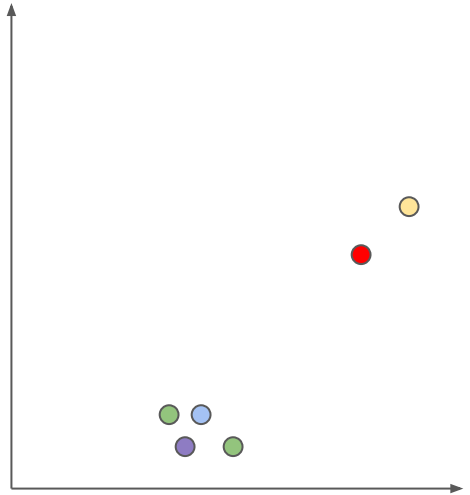

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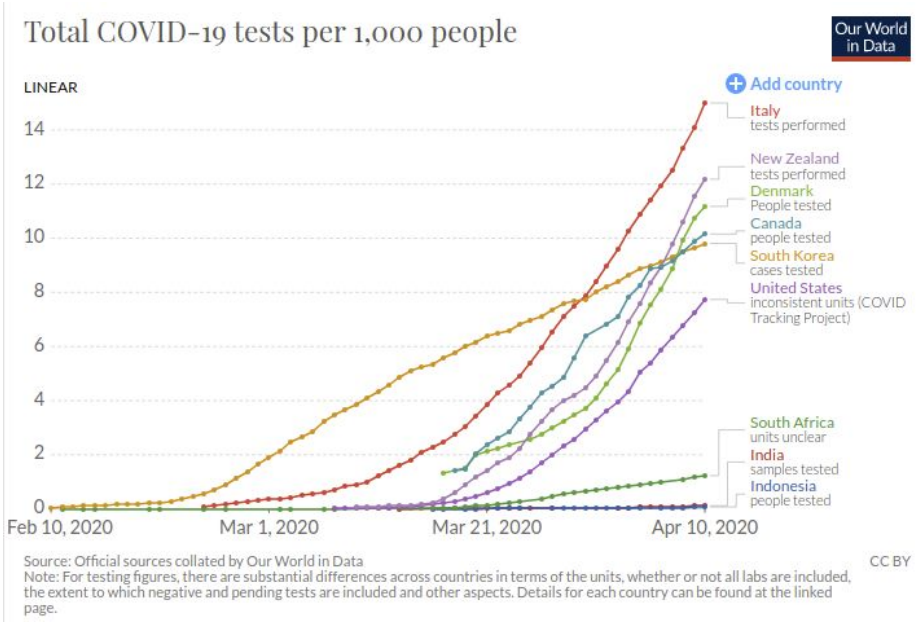

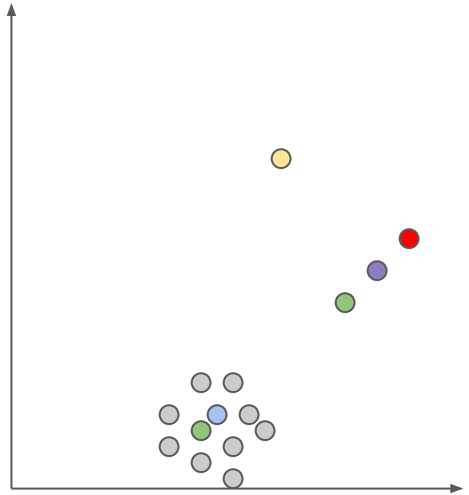

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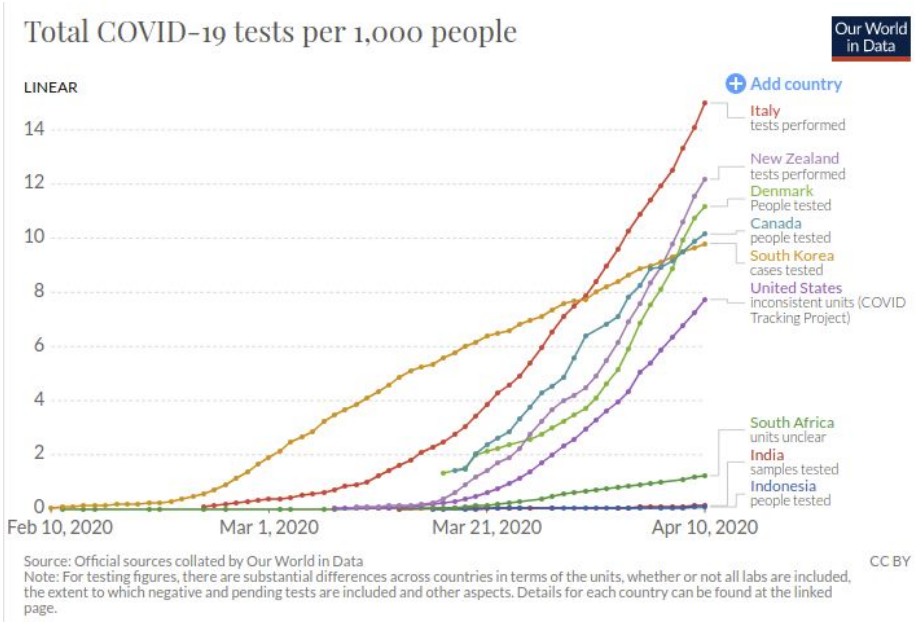

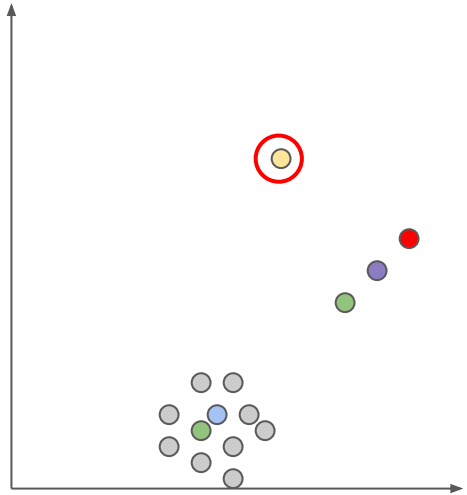

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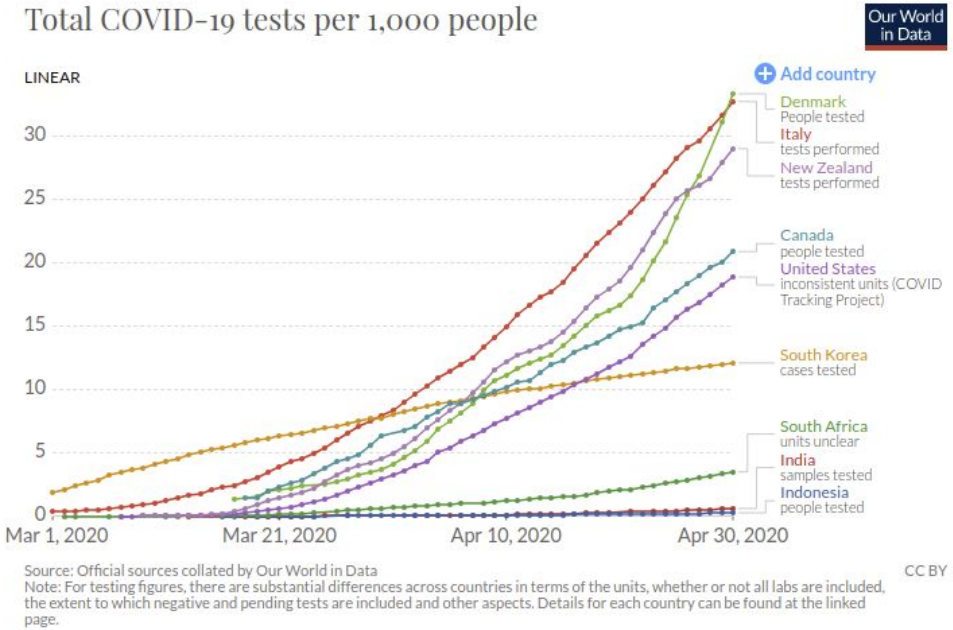
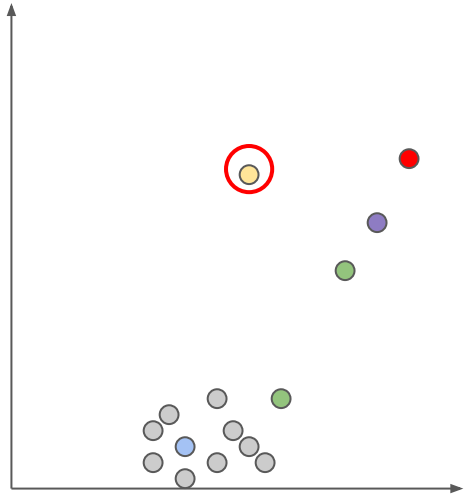
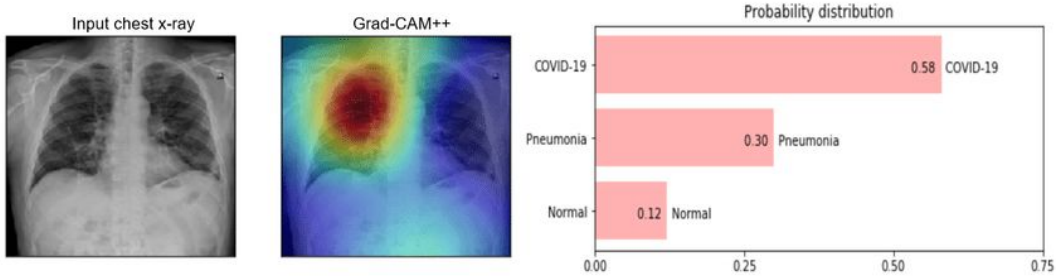




Data Source CNN

- rsna-pneumonia-detection-challenge*

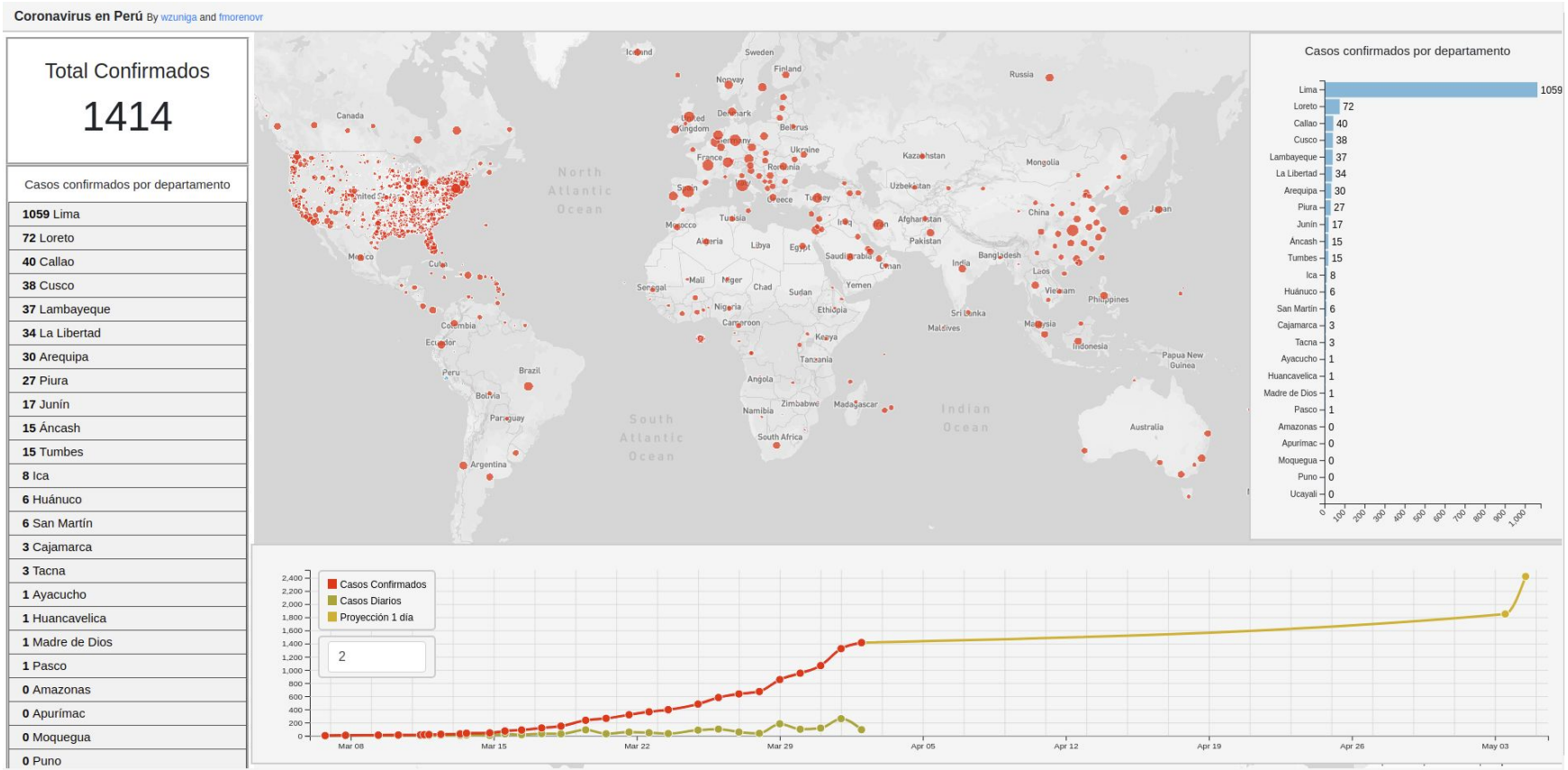


Sample of simple output of our expected classifier

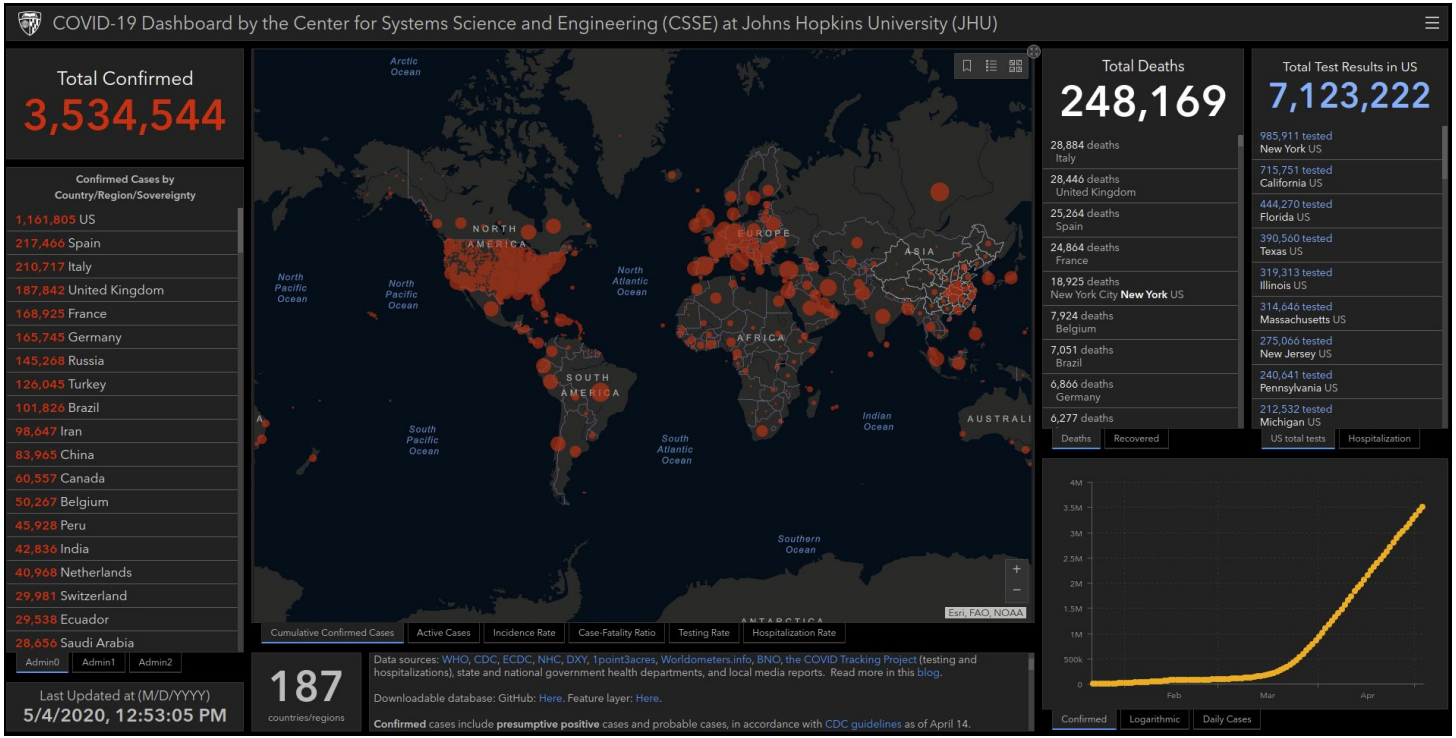
Source:

- * https://www.kaggle.com/c/rsna-pneumonia-detection-challenge
- https://arxiv.org/pdf/2004.04582.pdf

Visualization System

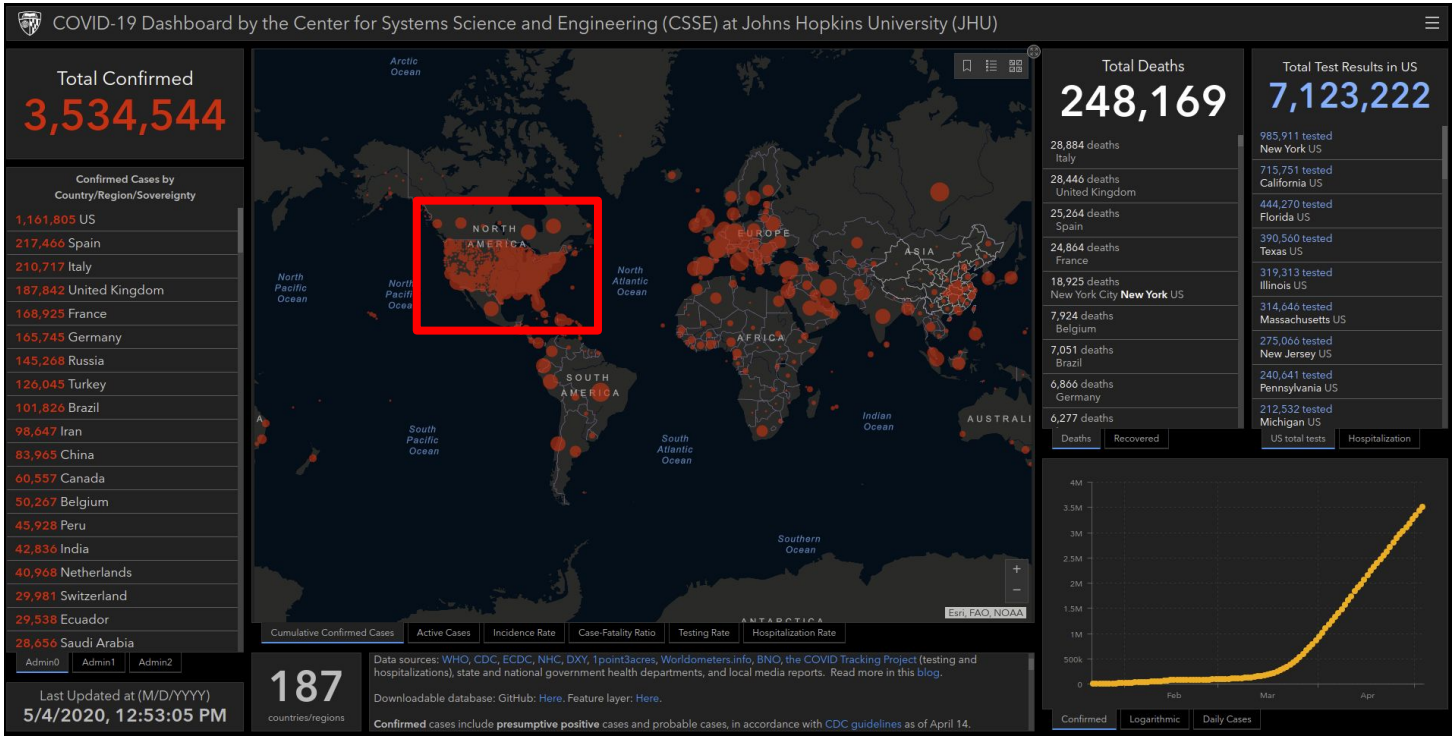


Visualization Problems



Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU)

Visualization Problems



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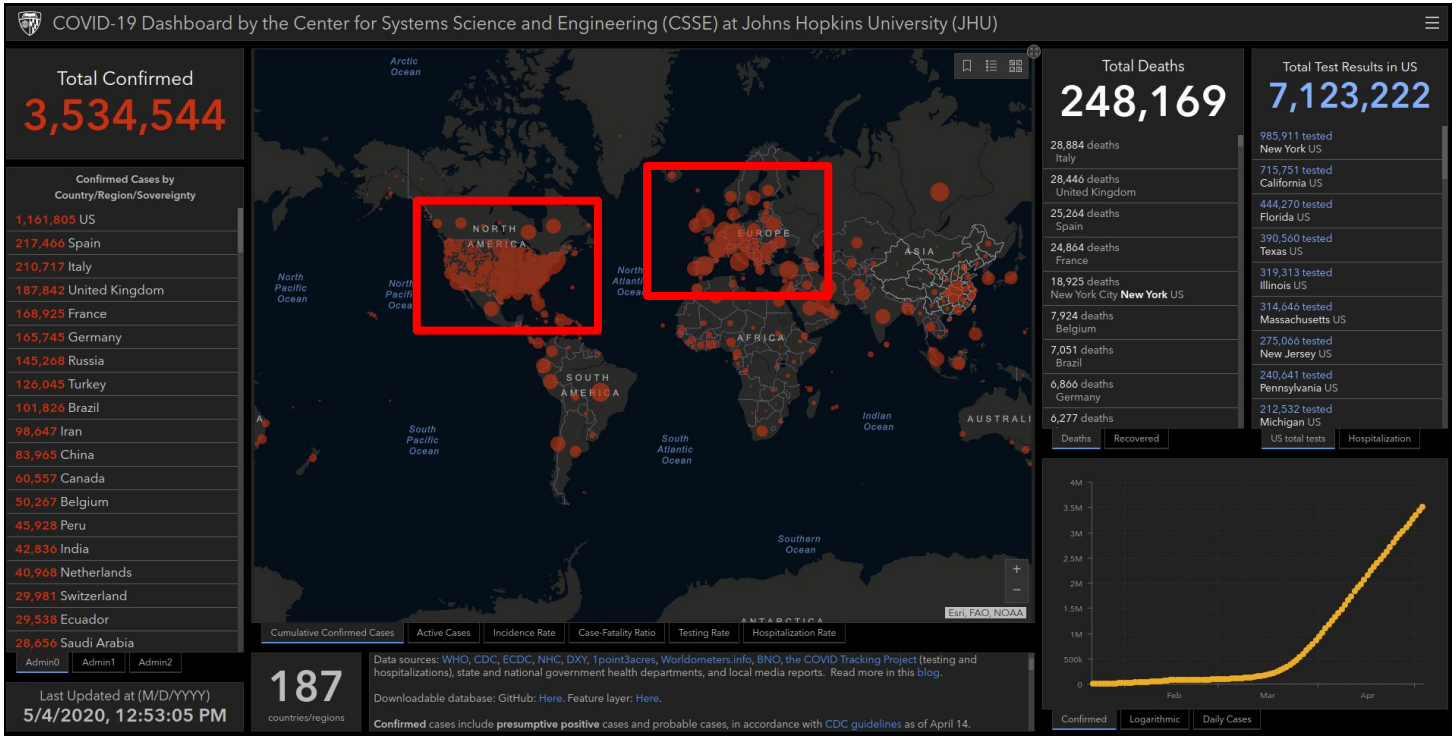
Visualization Problems



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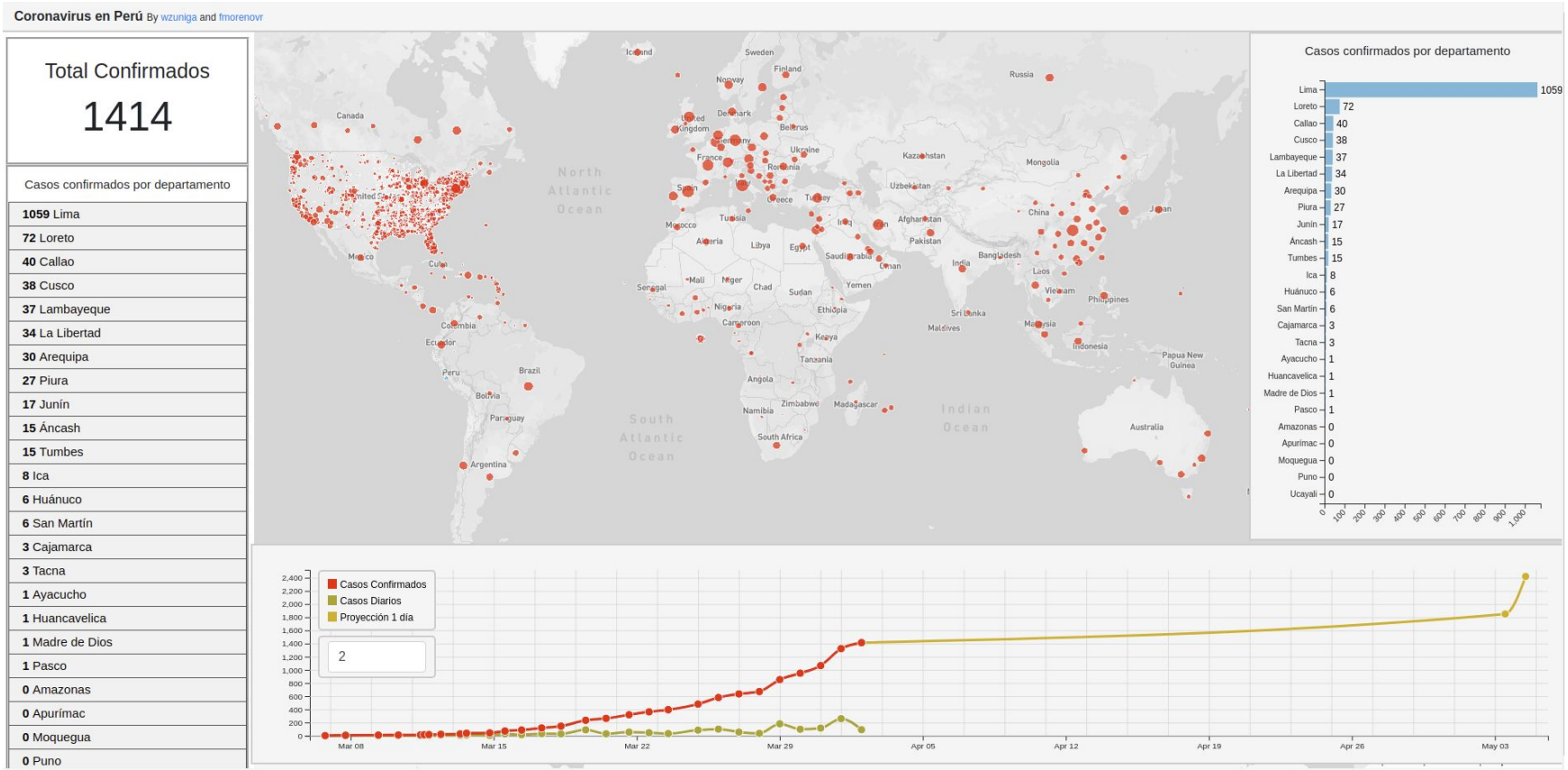
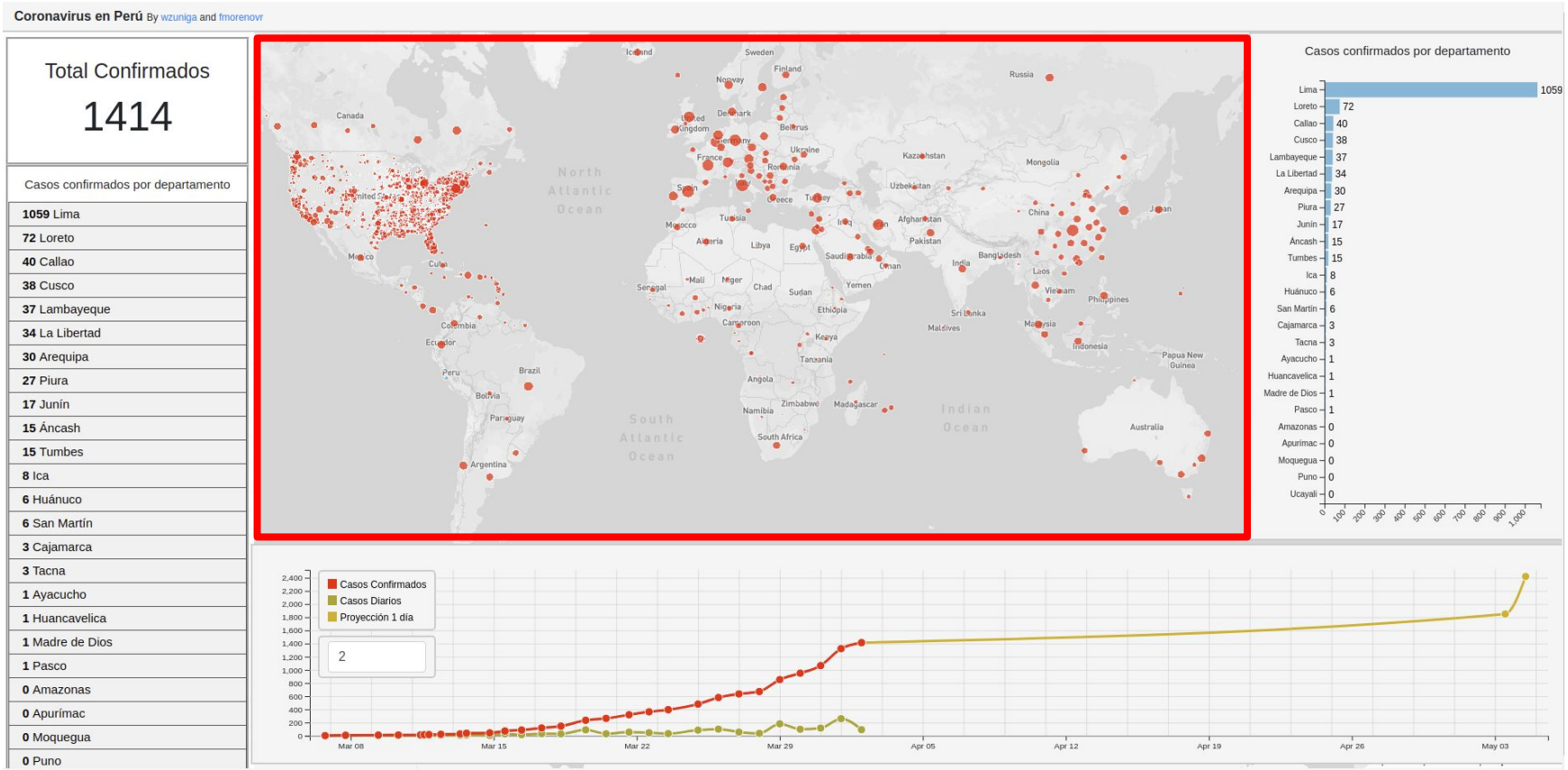
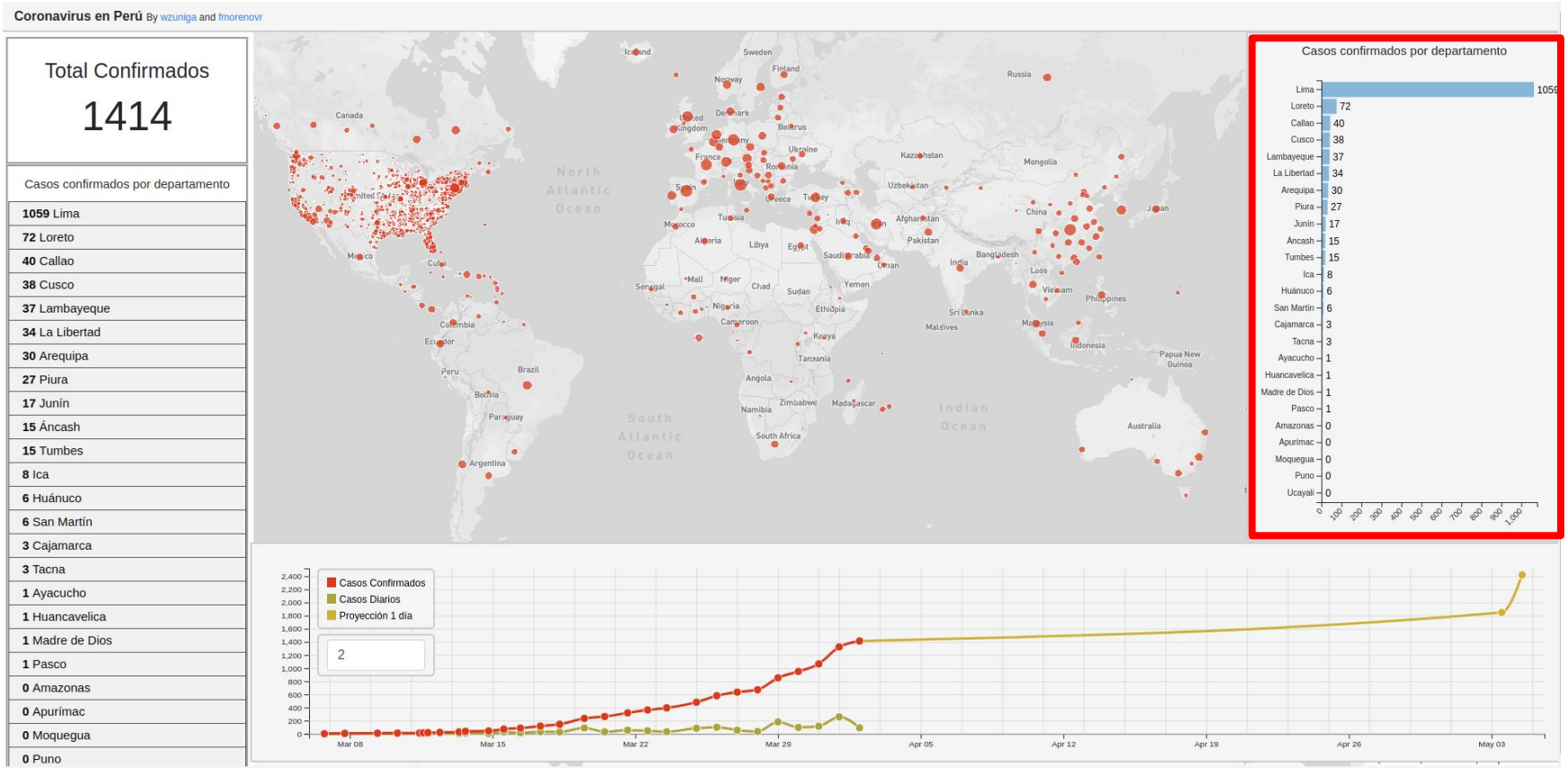
Visualization System



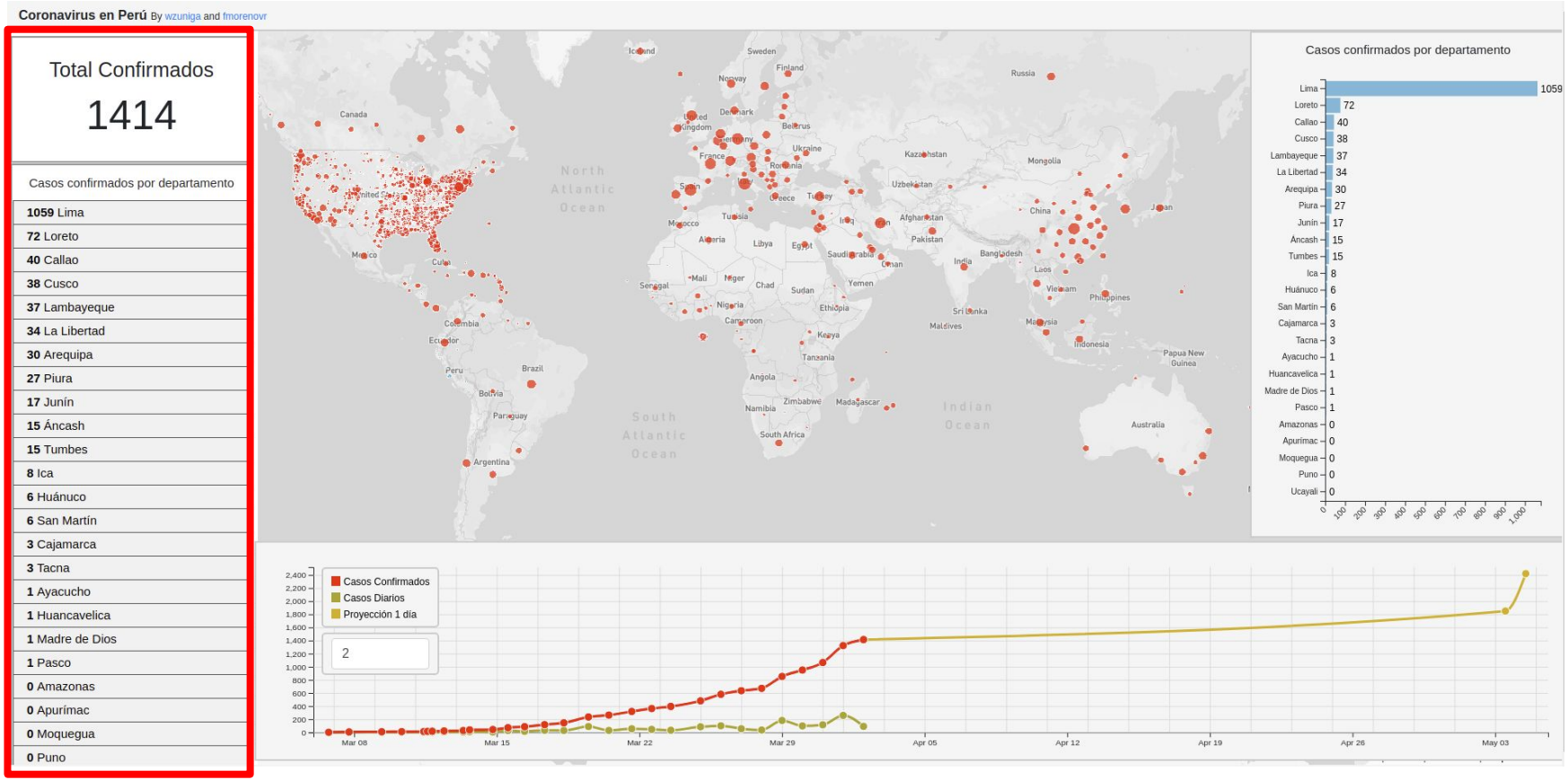
Visualization System



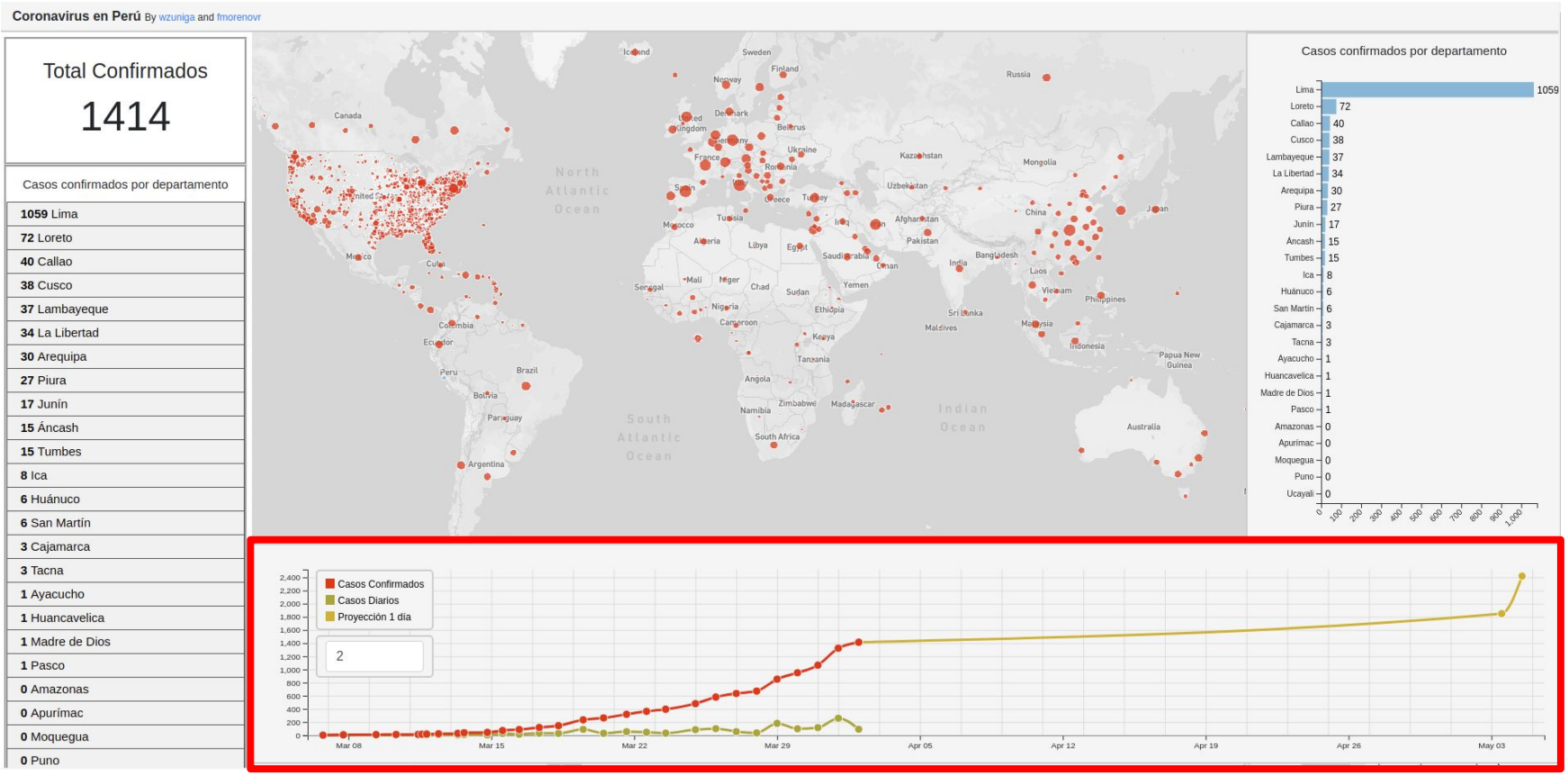
Visualization System



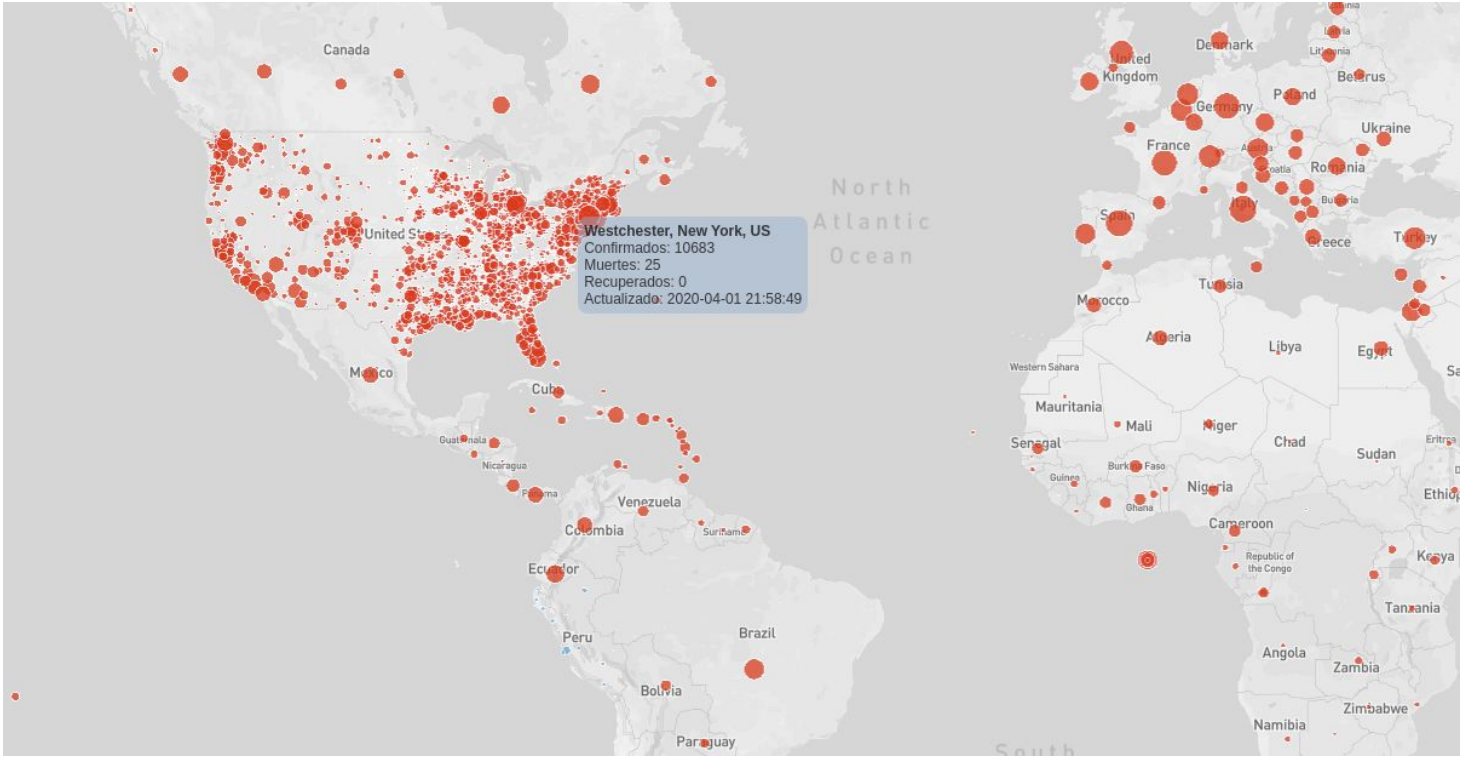
Visualization System



Visualization System



Show data


Canada
United States
Mexico
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