

Adaptabilidad

Ética

Derechos de autor

ChatGPT

Telemedicina

CURSO
INTRODUCTORIO A LA

INTELIGENCIA ARTIFICIAL

EN SALUD

Dirigido a:

- Profesionales y estudiantes de la ciencia de la Salud, Ingeniería y afines.
- Público en general.

28 DE ABRIL - 30 DE JUNIO

PONENTE:

Mg. Pablo Fonseca Arroyo
Director de Carrera - Ingeniería Informática
Universidad Peruana Cayetano Heredia

TEMA:

Relevancia de la IA para la salud



Rol de los profesionales de la salud y los pacientes

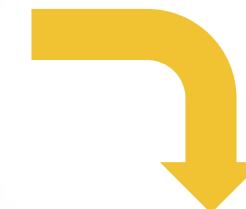
- Múltiples Roles involucrados
- Digitalización del sistema de salud
- Uso de inteligencia artificial para “problemas pequeños”
- Despliegue cuidadoso
- Evaluación y adaptación



Colaboración e investigación interdisciplinaria: Caso - Rayos X de tórax



Almacenamiento



Recuperación



Captura



PACS

Visualización

MIMIC Chest X-Ray Database (Febrero, 2019)

The image shows a screenshot of a news article from MIT News. The header features the MIT logo and the text "MIT News ON CAMPUS AND AROUND THE WORLD". Below the header is a large image of a chest X-ray. To the right of the X-ray, there is a text box containing the following information:

Researchers have released a repository of more than 350,000 detailed chest X-rays, which is free and open to academic, clinical, and industrial investigators.

Image courtesy of the researchers.

Below the image and text box, there is a summary of the news article:

MIMIC Chest X-Ray database to provide researchers access to over 350,000 patient radiographs

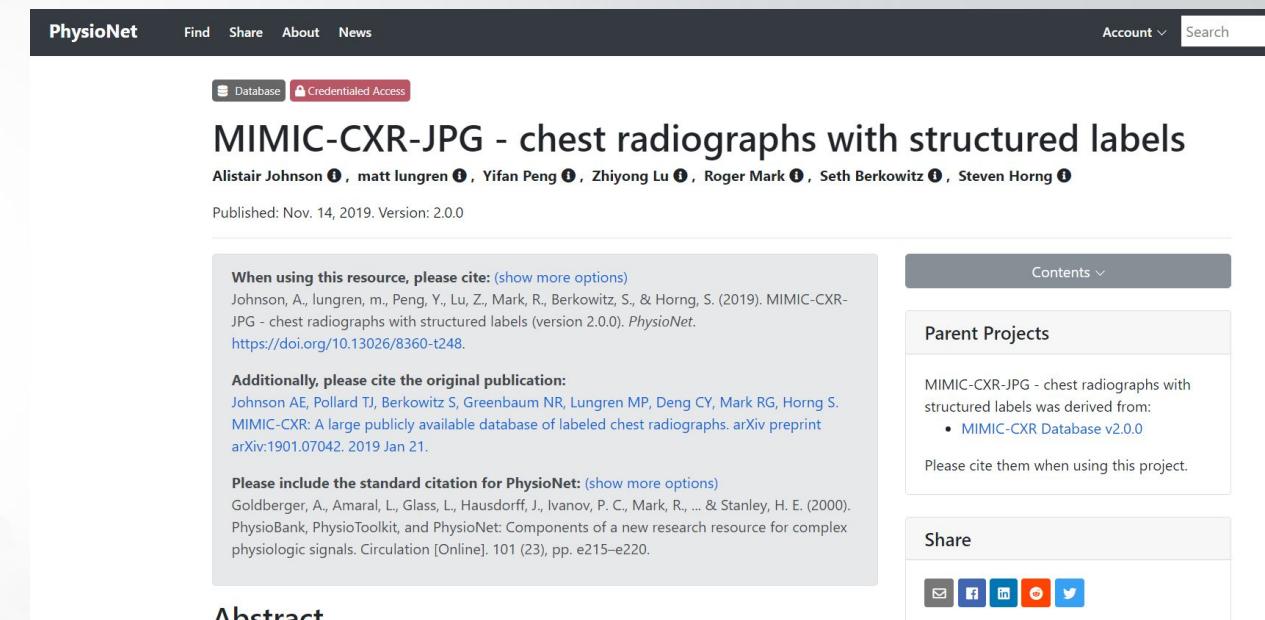
A new database of images could pave a path for algorithmic models that ensure accurate diagnoses of conditions like pneumonia.

At the bottom right of the screenshot, there is a blue link: <http://news.mit.edu/2019/mimic-chest-x-ray-database-0201>

MIMIC Chest X-Ray Database (Febrero, 2019)

- Los rayos x de tórax son el estudio de imágenes más común en el mundo
- 377,110 imágenes en formato JPG (producidas de los originales en DICOM)
- Las etiquetas fueron obtenidas de 227,827 informes de radiología

Johnson, A. E., Pollard, T. J., Greenbaum, N. R., Lungren, M. P., Deng, C. Y., Peng, Y., ... & Horng, S. (2019). MIMIC-CXR-JPG, a large publicly available database of labeled chest radiographs. *arXiv preprint arXiv:1901.07042*.



The screenshot shows the PhysioNet website with the following details:

- Header:** PhysioNet, Find, Share, About, News, Account, Search.
- Breadcrumbs:** Database > Credentialed Access > MIMIC-CXR-JPG - chest radiographs with structured labels.
- Title:** MIMIC-CXR-JPG - chest radiographs with structured labels
- Authors:** Alistair Johnson, matt lungren, Yifan Peng, Zhiyong Lu, Roger Mark, Seth Berkowitz, Steven Horng.
- Date:** Published: Nov. 14, 2019. Version: 2.0.0.
- Content:**
 - When using this resource, please cite:** (show more options)
Johnson, A., lungren, m., Peng, Y., Lu, Z., Mark, R., Berkowitz, S., & Horng, S. (2019). MIMIC-CXR-JPG - chest radiographs with structured labels (version 2.0.0). *PhysioNet*. <https://doi.org/10.13026/8360-t248>.
 - Additionally, please cite the original publication:**
Johnson AE, Pollard TJ, Berkowitz S, Greenbaum NR, Lungren MP, Deng CY, Mark RG, Horng S. MIMIC-CXR: A large publicly available database of labeled chest radiographs. *arXiv preprint arXiv:1901.07042*. 2019 Jan 21.
 - Please include the standard citation for PhysioNet:** (show more options)
Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation [Online]*, 101 (23), pp. e215–e220.
- Right sidebar:** Contents, Parent Projects, MIMIC-CXR-JPG - chest radiographs with structured labels was derived from:
 - MIMIC-CXR Database v2.0.0Please cite them when using this project.
- Share:** Email, Facebook, LinkedIn, Google+, Twitter.

<https://physionet.org/content/mimic-cxr-jpg/2.0.0/>

DICOM hacia JPEG

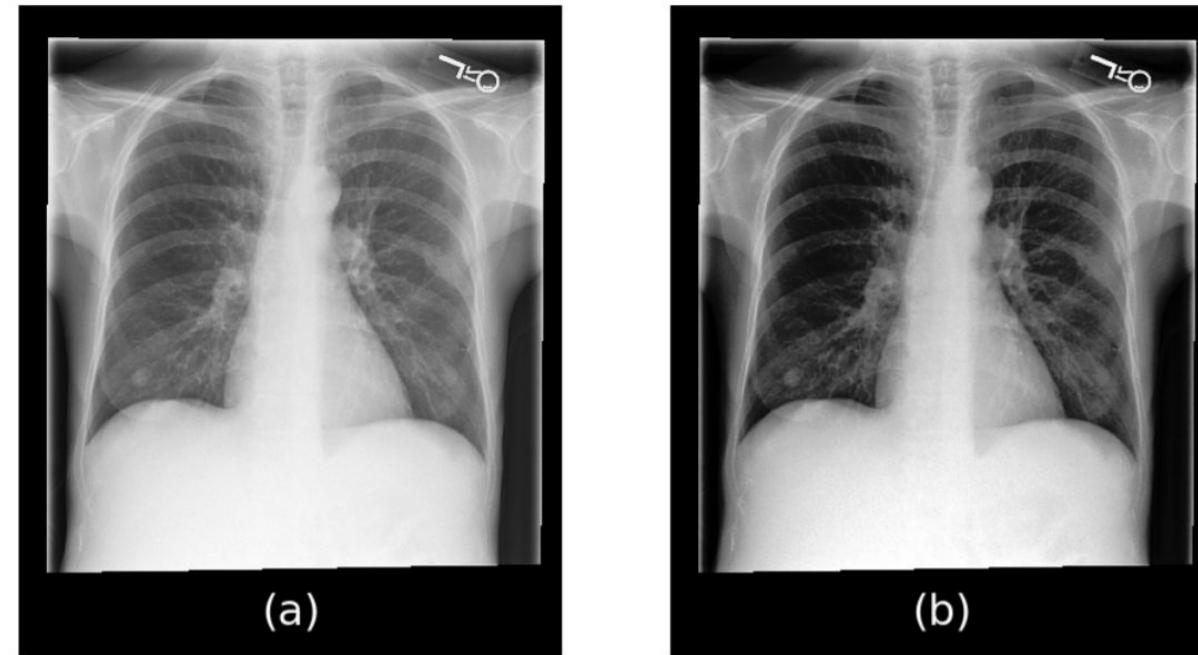


Figure 1: Example of an image converted from DICOM (a) to JPEG (b).

Johnson, A. E., Pollard, T. J., Greenbaum, N. R., Lungren, M. P., Deng, C. Y., Peng, Y., ... & Horng, S. (2019). MIMIC-CXR-JPG, a large publicly available database of labeled chest radiographs. *arXiv preprint arXiv:1901.07042*.

Construyendo “etiquetas” a partir de informes de texto semi-estructurado

- A veces los informes se encuentran en un formato semi-estructurado

| Section | Report | Label |
|------------|---|---|
| Impression | No evidence of acute cardiopulmonary process. | No Finding |
| Findings | The left lung is relatively well aerated and clear. The right hemithorax is markedly opacified with volume loss, circumferential pleural thickening and pleural fluid with near complete opacification of the right lung with right basal pleural catheter noted. Hydropneumothorax previously seen is not as well evaluated on this not fully upright film. Cardiac contours are somewhat obscured but unremarkable. | <i>No Cardiomegaly</i> <i>No Enlarged Cardiomediastinum</i> Pneumothorax ^u Airspace Opacity Pleural Effusion Pleural Other Support Devices |
| Other | Cardiac size is top normal. Bibasilar opacities, larger on the left side, could be due to atelectasis but superimposed infection cannot be excluded. If any, there is a small right pleural effusion. There is elevation of the right hemidiaphragm. There is mild vascular congestion. | <i>No Cardiomegaly</i> Atelectasis ^u Pneumonia ^u Edema ^u Airspace Opacity Pleural Effusion |

Johnson, A. E., Pollard, T. J., Greenbaum, N. R., Lungren, M. P., Deng, C. Y., Peng, Y., ... & Horng, S. (2019). MIMIC-CXR-JPG, a large publicly available database of labeled chest radiographs. *arXiv preprint arXiv:1901.07042*.

Construyendo “etiquetas” a partir de informes de texto semi-estructurado

Podemos ver las frecuencias de las etiquetas en el dataset

Table 2: Frequency of labels in MIMIC-CXR-JPG on the training subset of 222,750 unique radiologic studies (8 studies were not labeled).

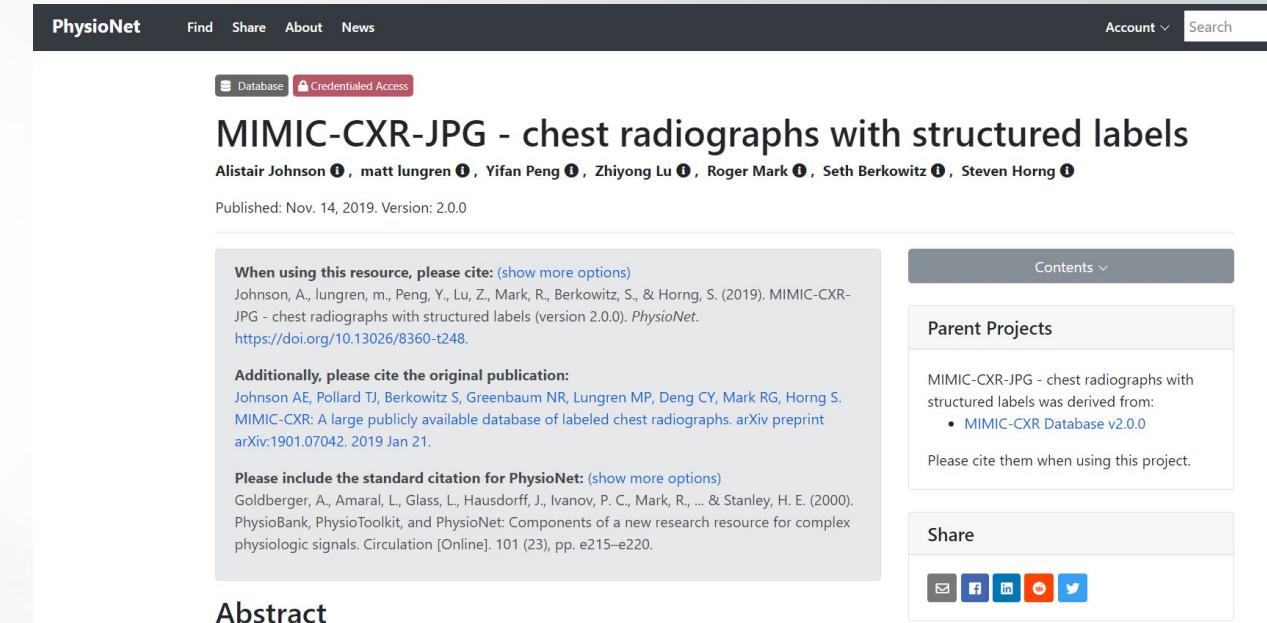
| | Positive | Negative | Uncertain | Disagreement |
|----------------------------|----------------|------------------|-----------------|--------------|
| Atelectasis | 45,088 (19.8%) | 937.0 (0.4%) | 9,897.0 (4.3%) | 1,744 (0.8%) |
| Cardiomegaly | 39,094 (17.2%) | 15,860.0 (7.0%) | 5,924.0 (2.6%) | 5,924 (2.6%) |
| Consolidation | 10,487 (4.6%) | 7,939.0 (3.5%) | 3,022.0 (1.3%) | 1,628 (0.7%) |
| Edema | 26,455 (11.6%) | 25,246.0 (11.1%) | 11,781.0 (5.2%) | 2,351 (1.0%) |
| Enlarged Cardiomediastinum | 7,004 (3.1%) | 5,271.0 (2.3%) | 9,307.0 (4.1%) | 255 (0.1%) |
| Fracture | 3,768 (1.7%) | 880.0 (0.4%) | 299.0 (0.1%) | 884 (0.4%) |
| Lung Lesion | 6,129 (2.7%) | 842.0 (0.4%) | 1,020.0 (0.4%) | 296 (0.1%) |
| Lung Opacity | 50,916 (22.3%) | 2,868.0 (1.3%) | 2,110.0 (0.9%) | 2,531 (1.1%) |
| No Finding | 75,163 (33.0%) | - | - | 3,906 (1.7%) |
| Pleural Effusion | 53,188 (23.3%) | 27,072.0 (11.9%) | 5,345.0 (2.3%) | 1,667 (0.7%) |
| Pleural Other | 1,961 (0.9%) | 120.0 (0.1%) | 728.0 (0.3%) | 93 (0.0%) |
| Pneumonia | 15,769 (6.9%) | 24,205.0 (10.6%) | 17,789.0 (7.8%) | 1,422 (0.6%) |
| Pneumothorax | 9,317 (4.1%) | 42,335.0 (18.6%) | 868.0 (0.4%) | 1,328 (0.6%) |
| Support Devices | 65,637 (28.8%) | 3,070.0 (1.3%) | 96.0 (0.0%) | 1,831 (0.8%) |

Johnson, A. E., Pollard, T. J., Greenbaum, N. R., Lungren, M. P., Deng, C. Y., Peng, Y., ... & Horng, S. (2019). MIMIC-CXR-JPG, a large publicly available database of labeled chest radiographs. *arXiv preprint arXiv:1901.07042*.

Disponibilidad de los datos

- Disponible a través de PhysioNet
- Libre acceso después de firmar un acuerdo de uso de datos
- El dataset original MIMIC-CXR contiene
 - imágenes DICOM
 - informes

Johnson, A. E., Pollard, T. J., Greenbaum, N. R., Lungren, M. P., Deng, C. Y., Peng, Y., ... & Horng, S. (2019). MIMIC-CXR-JPG, a large publicly available database of labeled chest radiographs. *arXiv preprint arXiv:1901.07042*.



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- Abstract:** When using this resource, please cite: (show more options) Johnson, A., lungren, m., Peng, Y., Lu, Z., Mark, R., Berkowitz, S., & Horng, S. (2019). MIMIC-CXR-JPG - chest radiographs with structured labels (version 2.0.0). *PhysioNet*. <https://doi.org/10.13026/8360-t248>. Additionally, please cite the original publication: Johnson AE, Pollard TJ, Berkowitz S, Greenbaum NR, Lungren MP, Deng CY, Mark RG, Horng S. MIMIC-CXR: A large publicly available database of labeled chest radiographs. *arXiv preprint arXiv:1901.07042*. 2019 Jan 21. Please include the standard citation for PhysioNet: (show more options) Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation [Online]*, 101 (23), pp. e215–e220.
- Side Panels:** Contents, Parent Projects, Share (with icons for email, Facebook, LinkedIn, YouTube, Twitter).

<https://physionet.org/content/mimic-cxr-jpg/2.0.0/>

Base de datos: CheXPERT

- 224,316 radiografías de 65,240 pacientes
- 14 observaciones comunes



Irvin, J., Rajpurkar, P., Ko, M., Yu, Y., Ciurea-Ilcus, S., Chute, C., ... & Seekins, J. (2019, July). CheXpert: A large chest radiograph dataset with uncertainty labels and expert comparison. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 33, pp. 590-597).



What is CheXpert?

CheXpert is a large dataset of chest X-rays and competition for automated chest x-ray interpretation, which features uncertainty labels and radiologist-labeled reference standard evaluation sets.

[READ THE PAPER \(IRVIN & RAJPURKAR ET AL.\)](#)

Why CheXpert?

Chest radiography is the most common imaging examination globally, critical for screening, diagnosis, and management of many life threatening diseases. Automated chest radiograph interpretation at the level of practicing radiologists

Leaderboard

Will your model perform as well as radiologists in detecting different pathologies in chest X-rays?

| Rank | Date | Model | AUC | Num Rads Below Curve |
|------|--------------|--|-------|----------------------|
| 1 | Sep 01, 2019 | Hierarchical-Learning-V1 (ensemble) Vingroup Big Data Institute https://arxiv.org/abs/1911.06475 | 0.930 | 2.6 |

<https://stanfordmlgroup.github.io/competitions/chexpert/>

Construyendo “etiquetas” a partir de informes de texto semi-estructurado

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Irvin, J., Rajpurkar, P., Ko, M., Yu, Y., Ciurea-Ilcus, S., Chute, C., ... & Seekins, J. (2019, July). CheXpert: A large chest radiograph dataset with uncertainty labels and expert comparison. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 33, pp. 590-597).

| Pathology | Positive (%) | Uncertain (%) | Negative (%) |
|-------------------|---------------|---------------|----------------|
| No Finding | 16627 (8.86) | 0 (0.0) | 171014 (91.14) |
| Enlarged Cardiom. | 9020 (4.81) | 10148 (5.41) | 168473 (89.78) |
| Cardiomegaly | 23002 (12.26) | 6597 (3.52) | 158042 (84.23) |
| Lung Lesion | 6856 (3.65) | 1071 (0.57) | 179714 (95.78) |
| Lung Opacity | 92669 (49.39) | 4341 (2.31) | 90631 (48.3) |
| Edema | 48905 (26.06) | 11571 (6.17) | 127165 (67.77) |
| Consolidation | 12730 (6.78) | 23976 (12.78) | 150935 (80.44) |
| Pneumonia | 4576 (2.44) | 15658 (8.34) | 167407 (89.22) |
| Atelectasis | 29333 (15.63) | 29377 (15.66) | 128931 (68.71) |
| Pneumothorax | 17313 (9.23) | 2663 (1.42) | 167665 (89.35) |
| Pleural Effusion | 75696 (40.34) | 9419 (5.02) | 102526 (54.64) |
| Pleural Other | 2441 (1.3) | 1771 (0.94) | 183429 (97.76) |
| Fracture | 7270 (3.87) | 484 (0.26) | 179887 (95.87) |
| Support Devices | 105831 (56.4) | 898 (0.48) | 80912 (43.12) |

Table 1: The CheXpert dataset consists of 14 labeled observations. We report the number of studies which contain these observations in the training set.

Detectar casos fuera-de-la-distribución de entrenamiento

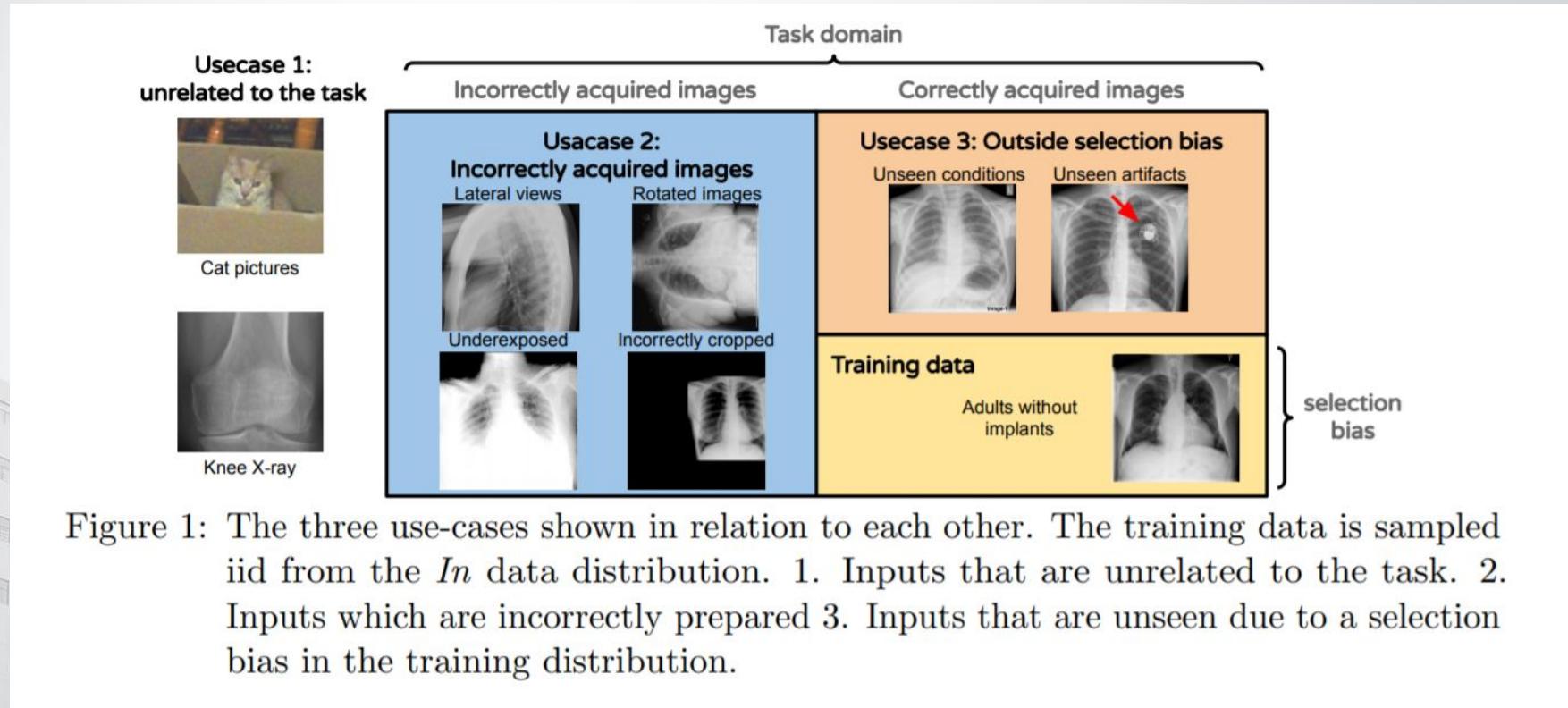


Figure 1: The three use-cases shown in relation to each other. The training data is sampled iid from the *In* data distribution. 1. Inputs that are unrelated to the task. 2. Inputs which are incorrectly prepared 3. Inputs that are unseen due to a selection bias in the training distribution.

Cao, T., Huang, C., Hui, D. Y. T., & Cohen, J. P. (2020). **A Benchmark of Medical Out of Distribution Detection.** *arXiv preprint arXiv:2007.04250*.

Explicación de la decisión

- Una vez identificados los casos que pertenecen a la distribución de entrenamiento, el algoritmo produce un mapa de calor para atribuir una explicación de las regiones que generan la predicción

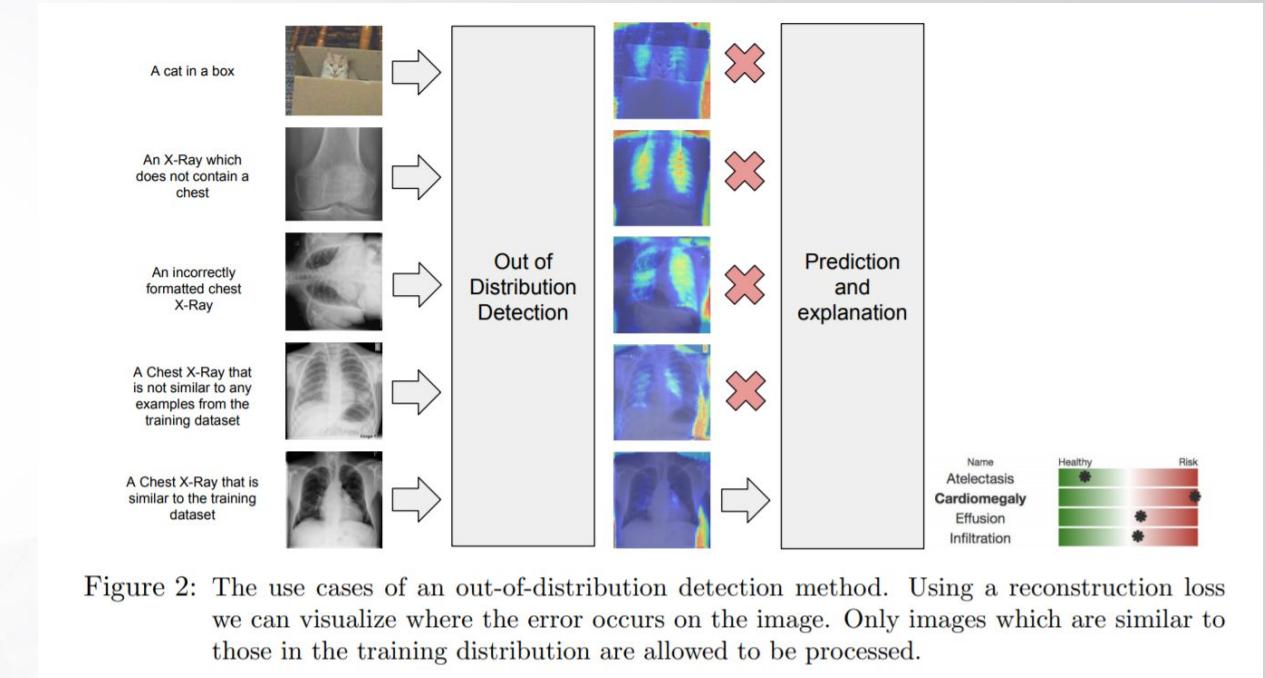


Figure 2: The use cases of an out-of-distribution detection method. Using a reconstruction loss we can visualize where the error occurs on the image. Only images which are similar to those in the training distribution are allowed to be processed.

Cohen, J. P., Bertin, P., & Frappier, V. (2019). **Chester: A Web Delivered Locally Computed Chest X-Ray Disease Prediction System**. *arXiv preprint arXiv:1901.11210*.

Explicación de la decisión

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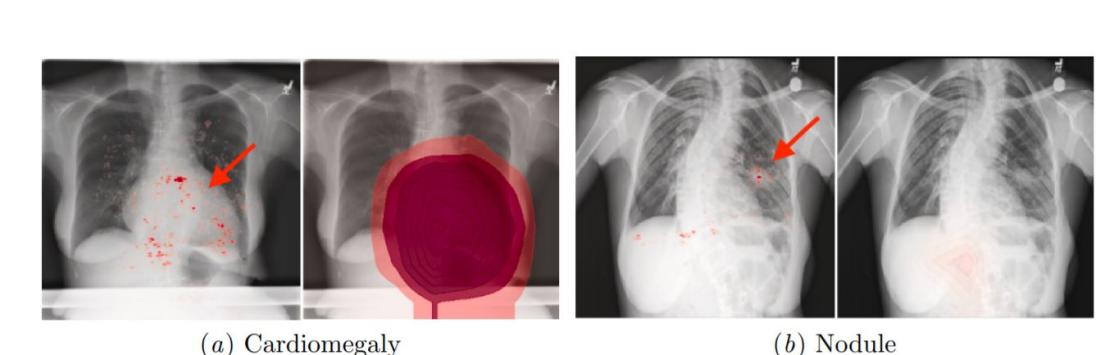


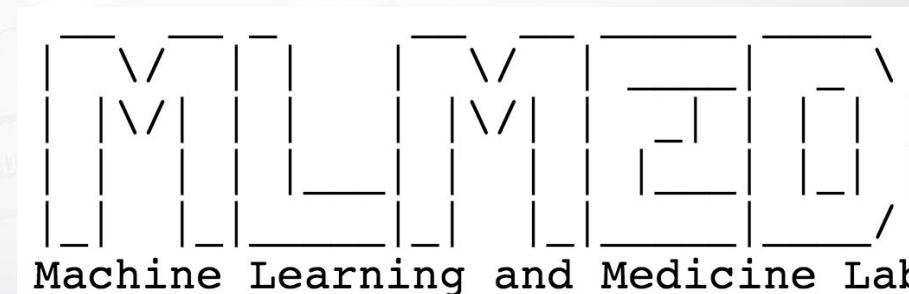
Figure 7: Example of localization using the two different mappings on two images. In each subfigure Left: Saliency Map. Right: Class Activation Map. The more red a region is the more of an impact of that region. Transparent pixels have negligible impact on the prediction.

Cohen, J. P., Bertin, P., & Frappier, V. (2019). **Chester: A Web Delivered Locally Computed Chest X-Ray Disease Prediction System**. *arXiv preprint arXiv:1901.11210*.

Caso: Rayos de X de tórax

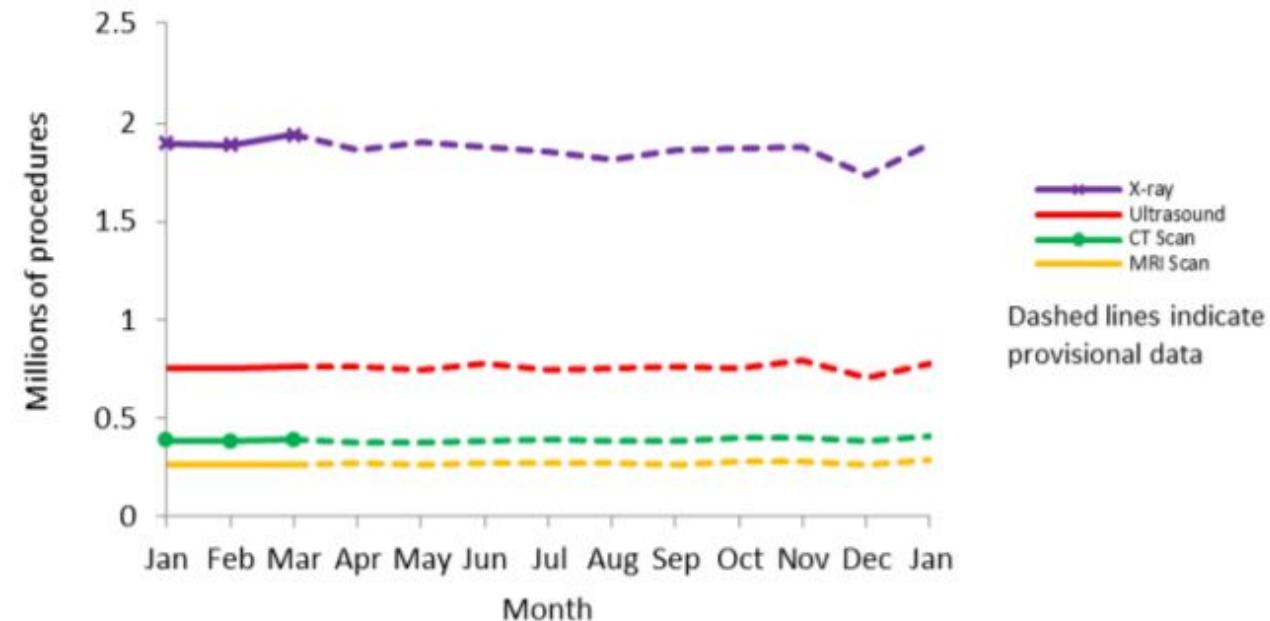


Chester the AI Radiology Assistant



Caso: Rayos de X de tórax

Graph 1: NHS imaging activity in England, January 2016 to January 2017



Further information on the tests included in these tables is given in the glossary section. Full break-downs by modality, provider and referral source setting are given in Tables 1a – 6j (separate excel files), available from
<http://www.england.nhs.uk/statistics/statistical-work-areas/diagnostic-imaging-dataset/>

<https://www.england.nhs.uk/statistics/wp-content/uploads/sites/2/2016/08/Provisional-Monthly-Diagnostic-Imaging-Dataset-Statistics-2017-05-18.pdf>

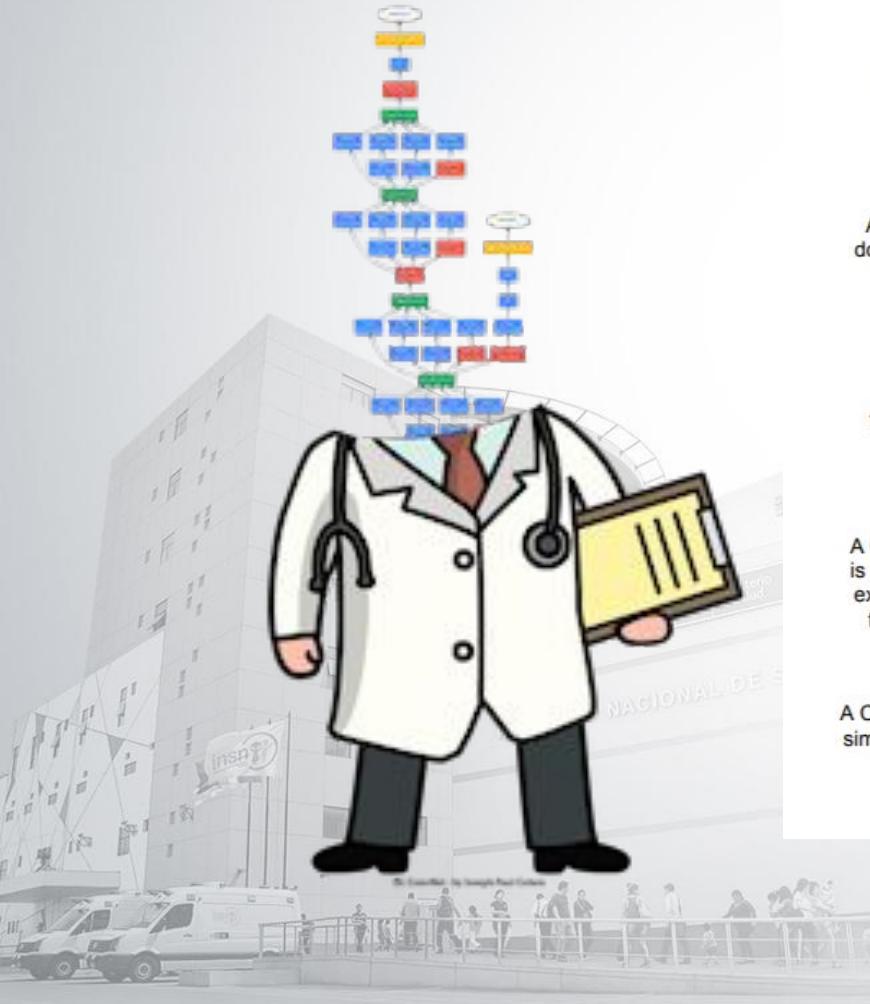
Caso: Rayos X de tórax

Table 1: Count of imaging activity in England, on NHS Patients, January 2016 to January 2017

| | X-ray | Ultrasound | CT Scan | MRI | Fluoro-scropy | Nuclear Medicine | PET-CT Scans | SPECT Scans | Medical Photography | % organisations included | Total ¹ |
|--------------------------|-------------------|------------------|------------------|------------------|------------------|------------------|----------------|---------------|---------------------|--------------------------|--------------------|
| Jan | 1,896,235 | 754,355 | 385,185 | 265,765 | 84,910 | 36,365 | 9,080 | 2,195 | 2,255 | 100.0% | 3,436,350 |
| Feb | 1,890,215 | 755,055 | 380,125 | 262,350 | 86,225 | 36,900 | 9,635 | 2,350 | 2,405 | 100.0% | 3,425,255 |
| Mar | 1,941,805 | 760,560 | 388,385 | 263,115 | 86,385 | 35,735 | 9,400 | 2,270 | 1,875 | 99.4% | 3,489,530 |
| Apr² | 1,860,290 | 762,845 | 378,340 | 268,375 | 86,005 | 35,205 | 10,570 | 2,270 | 2,620 | 97.1% | 3,406,525 |
| May | 1,907,055 | 745,505 | 372,615 | 260,365 | 84,365 | 33,405 | 10,200 | 2,125 | 2,520 | 95.4% | 3,418,160 |
| Jun | 1,883,265 | 775,225 | 383,720 | 268,640 | 90,095 | 35,995 | 10,755 | 2,215 | 2,535 | 97.1% | 3,452,440 |
| Jul | 1,859,080 | 747,505 | 389,340 | 271,520 | 85,845 | 34,435 | 10,020 | 2,715 | 2,130 | 98.9% | 3,402,590 |
| Aug | 1,814,660 | 756,390 | 387,305 | 269,330 | 85,630 | 34,285 | 10,495 | 2,730 | 2,430 | 98.3% | 3,363,255 |
| Sep | 1,861,830 | 763,710 | 387,390 | 266,965 | 87,920 | 34,715 | 10,770 | 2,820 | 2,700 | 98.9% | 3,418,820 |
| Oct | 1,874,155 | 757,355 | 398,325 | 277,650 | 85,615 | 34,765 | 10,870 | 2,780 | 2,545 | 98.9% | 3,444,050 |
| Nov | 1,877,695 | 793,925 | 400,815 | 282,440 | 91,105 | 36,720 | 11,300 | 3,115 | 2,765 | 98.3% | 3,499,885 |
| Dec | 1,734,760 | 706,835 | 384,650 | 260,600 | 78,655 | 31,365 | 10,265 | 2,625 | 2,395 | 97.7% | 3,212,150 |
| Jan | 1,893,240 | 774,325 | 404,050 | 283,345 | 85,410 | 34,690 | 11,355 | 3,000 | 2,915 | 96.0% | 3,492,320 |
| Total³ | 22,398,045 | 9,099,225 | 4,655,065 | 3,234,690 | 1,033,250 | 418,220 | 125,640 | 31,015 | 29,835 | - | 41,024,980 |

1. Total calculated as the sum of all activity for that month. Totals may not always equal the sum of the parts due to rounding. Activity not matched to a known organisation is omitted.
2. Data from April 2016 onwards are provisional and may be subject to change.
3. Total row represents a rolling 12 month total and does not include activity from the earliest month in the table. Totals may not always equal the sum of the parts due to rounding.

Caso: Rayos de X de tórax



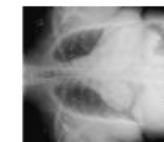
A cat in a box



An X-Ray which does not contain a chest



An incorrectly formatted chest X-Ray



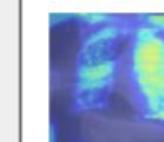
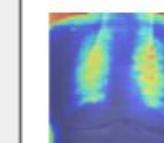
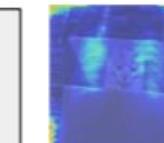
A Chest X-Ray that is not similar to any examples from the training dataset



A Chest X-Ray that is similar to the training dataset



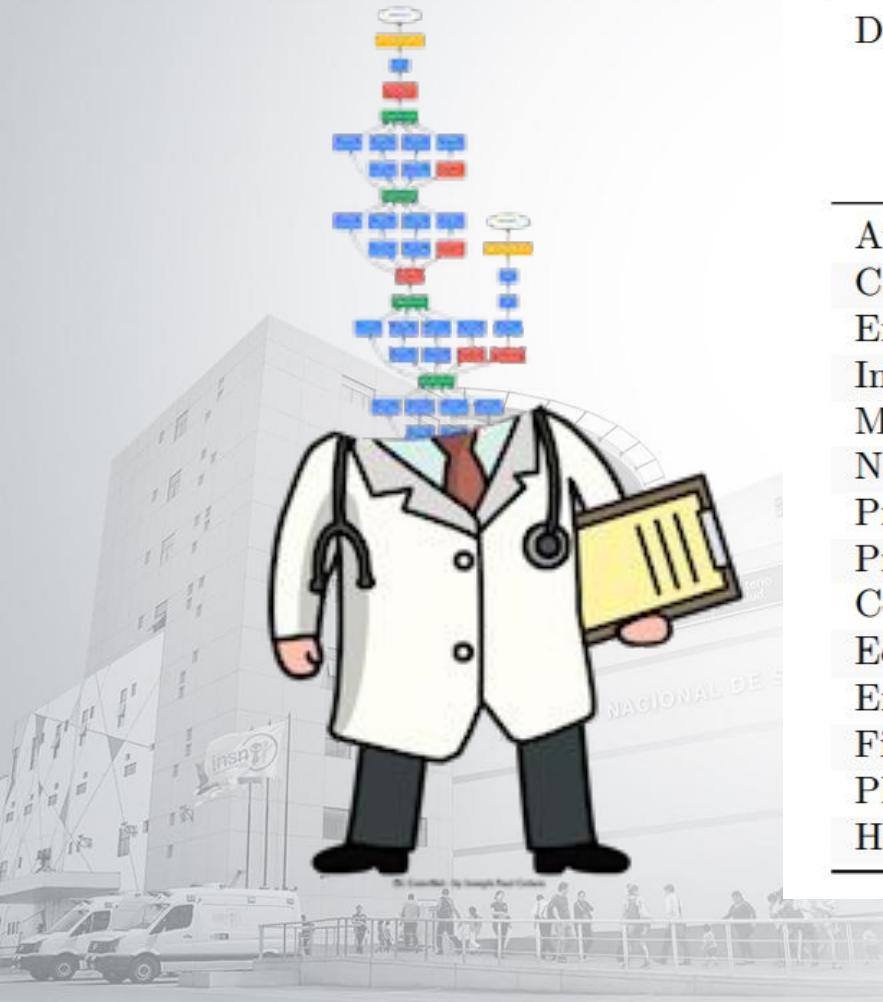
Out of Distribution Detection



Prediction and explanation



Caso: Rayos de X de tórax



| Disease | ChestX-ray14 Wang et al. (2017) DenseNet-50 | CheXNet Rajpurkar et al. (2017) DenseNet-121 | CheXNet Py3 Weng et al. (2017) DenseNet-121 | CheXNet Ours 45d rot 15%trans/15%scale DenseNet-121 |
|--------------------|--|---|--|--|
| Atelectasis | 0.71 | 0.80 | 0.81 ± 0.01 | 0.84 ± 0.01 |
| Cardiomegaly | 0.80 | 0.92 | 0.90 ± 0.01 | 0.92 ± 0.01 |
| Effusion | 0.78 | 0.86 | 0.87 ± 0.01 | 0.88 ± 0.01 |
| Infiltration | 0.60 | 0.73 | 0.70 ± 0.01 | 0.73 ± 0.01 |
| Mass | 0.70 | 0.86 | 0.82 ± 0.01 | 0.87 ± 0.01 |
| Nodule | 0.67 | 0.78 | 0.74 ± 0.01 | 0.79 ± 0.01 |
| Pneumonia | 0.63 | 0.76 | 0.76 ± 0.02 | 0.72 ± 0.04 |
| Pneumothorax | 0.80 | 0.88 | 0.83 ± 0.01 | 0.86 ± 0.01 |
| Consolidation | 0.70 | 0.79 | 0.79 ± 0.01 | 0.81 ± 0.01 |
| Edema | 0.83 | 0.88 | 0.86 ± 0.01 | 0.91 ± 0.01 |
| Emphysema | 0.81 | 0.93 | 0.89 ± 0.01 | 0.93 ± 0.01 |
| Fibrosis | 0.76 | 0.80 | 0.78 ± 0.01 | 0.78 ± 0.01 |
| Pleural Thickening | 0.70 | 0.80 | 0.75 ± 0.01 | 0.81 ± 0.01 |
| Hernia | 0.76 | 0.91 | 0.88 ± 0.03 | 0.83 ± 0.07 |

Caso: Rayos de X de tórax

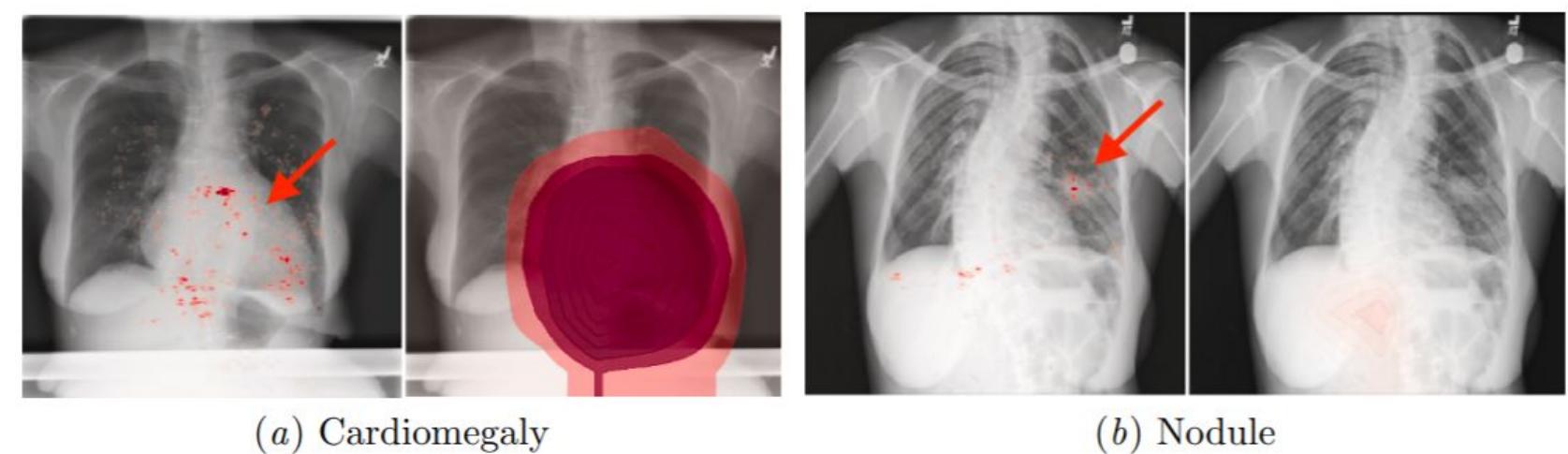
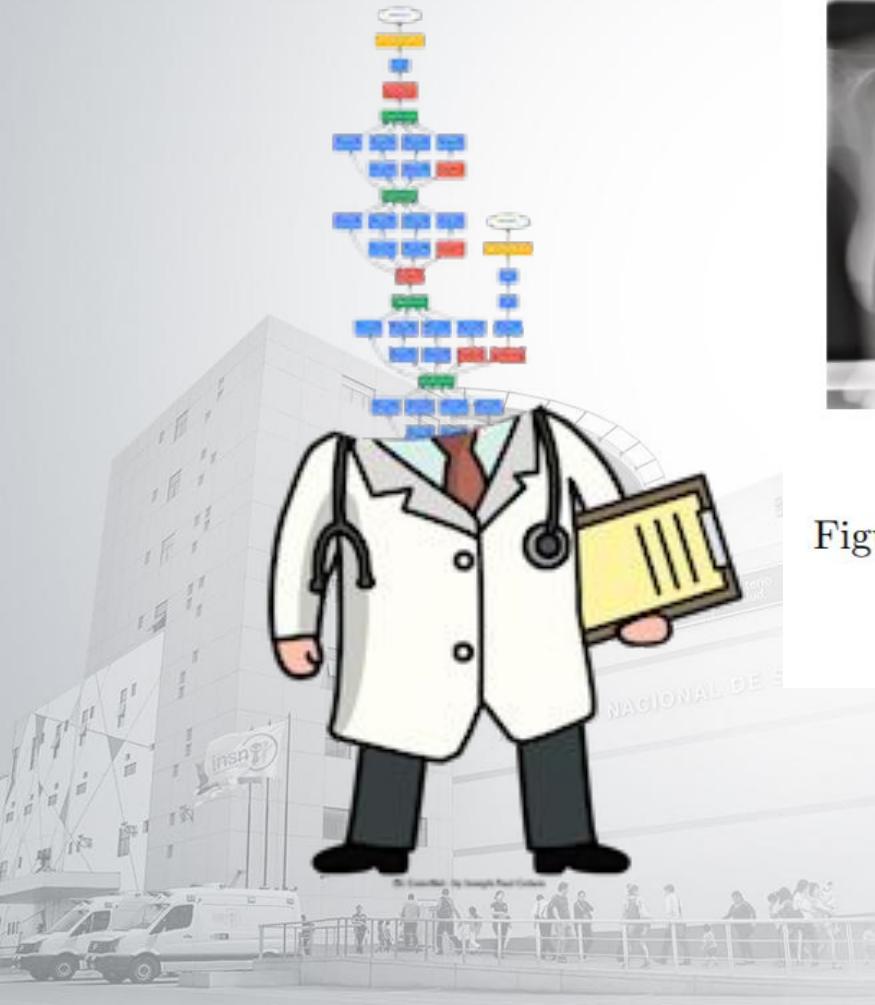


Figure 7: Example of localization using the two different mappings on two images. In each subfigure Left: Saliency Map. Right: Class Activation Map. The more red a region is the more of an impact of that region. Transparent pixels have negligible impact on the prediction.

Oportunidades y desafíos para la innovación: Integración

Cada Perfil de Integración IHE describe una necesidad clínica de integración de sistemas y la solución para llevarla a cabo. Define también los componentes funcionales, a los que llamaremos Actores IHE, y especifica con el mayor grado de detalle posible las transacciones que cada Actor deberá llevar a cabo, basadas siempre en estándares como el de Digital Imaging and Communication in Medicine (**DICOM**) y Health Level 7 (**HL7**).

¿Qué es un perfil de integración?

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¿Qué es un perfil de integración?

La verdadera motivación de las herramientas



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¿Qué es HL7?

- Health Level 7 - un estándar para intercambio de mensajes de informática médica



¿Qué es DICOM?

- D.I.C.O.M. son las siglas (en inglés) de **Estándar para el Tratamiento Digitales de Imágenes y Comunicaciones en Medicina** y fue establecido en 1992
- Basado en el estándar ACR-NEMA, publicado por primera vez en 1985
- DICOM 3.0 muestra que es la evolución de ACR-NEMA 1.0 y 2.0



DICOM Conformance Statement



- El Documento **DICOM Conformance Statement** es como un contrato.
- Muestra todas las clases SOP soportada por el producto.
- Describe detalles de la implementación.

Comunicación DICOM

- El protocolo permite dos equipos que soportan “DICOM” comunicarse: negociación e intercambio
- La negociación es importante para saber si el receptor puede manejar el tipo de mensaje.



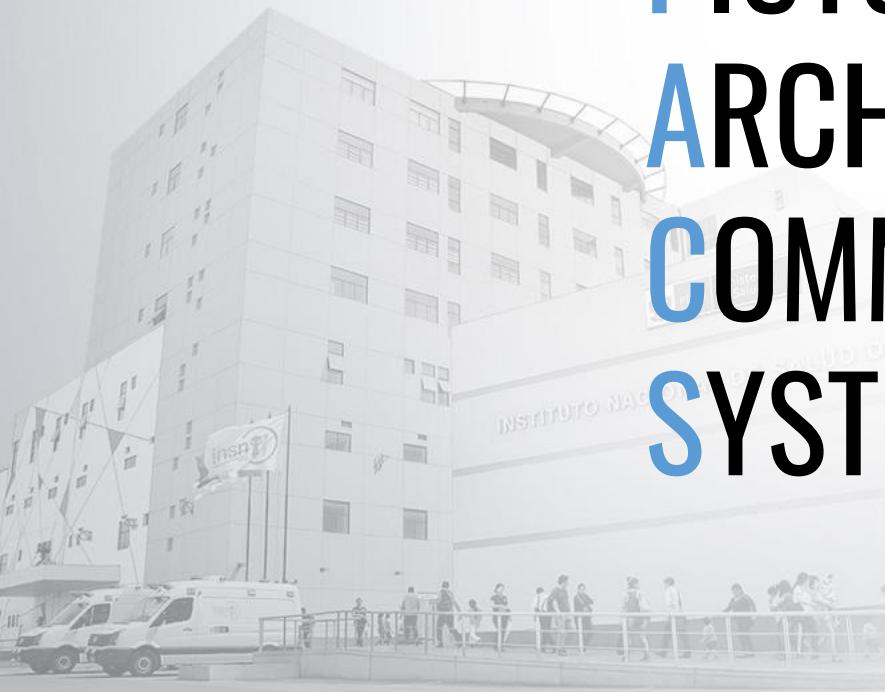
PACS

Es un sistema de almacenamiento y comunicación de imágenes (médicas)



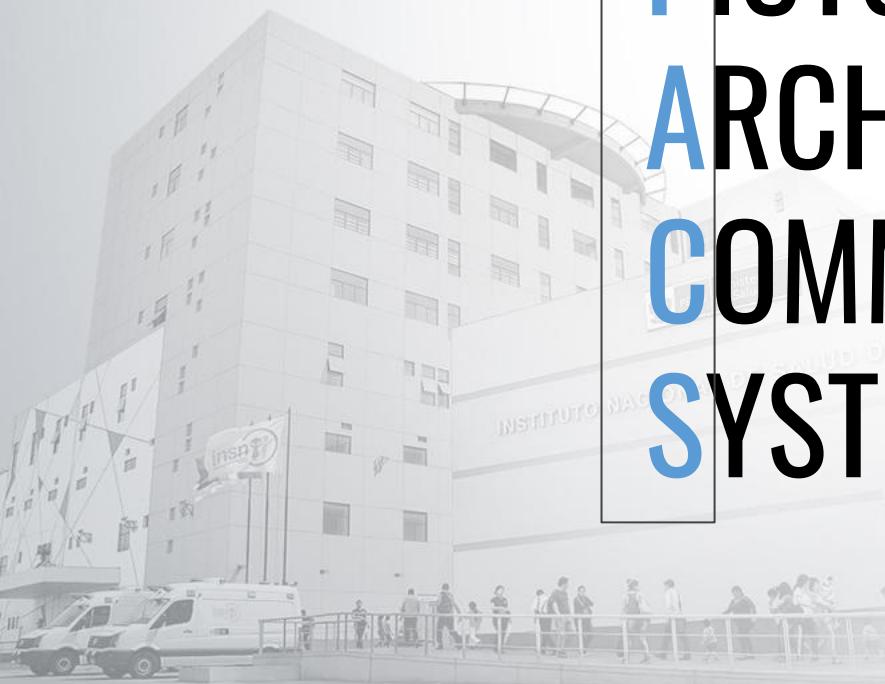
PACS

PICTURE ARCHIVING AND COMMUNICATION SYSTEM

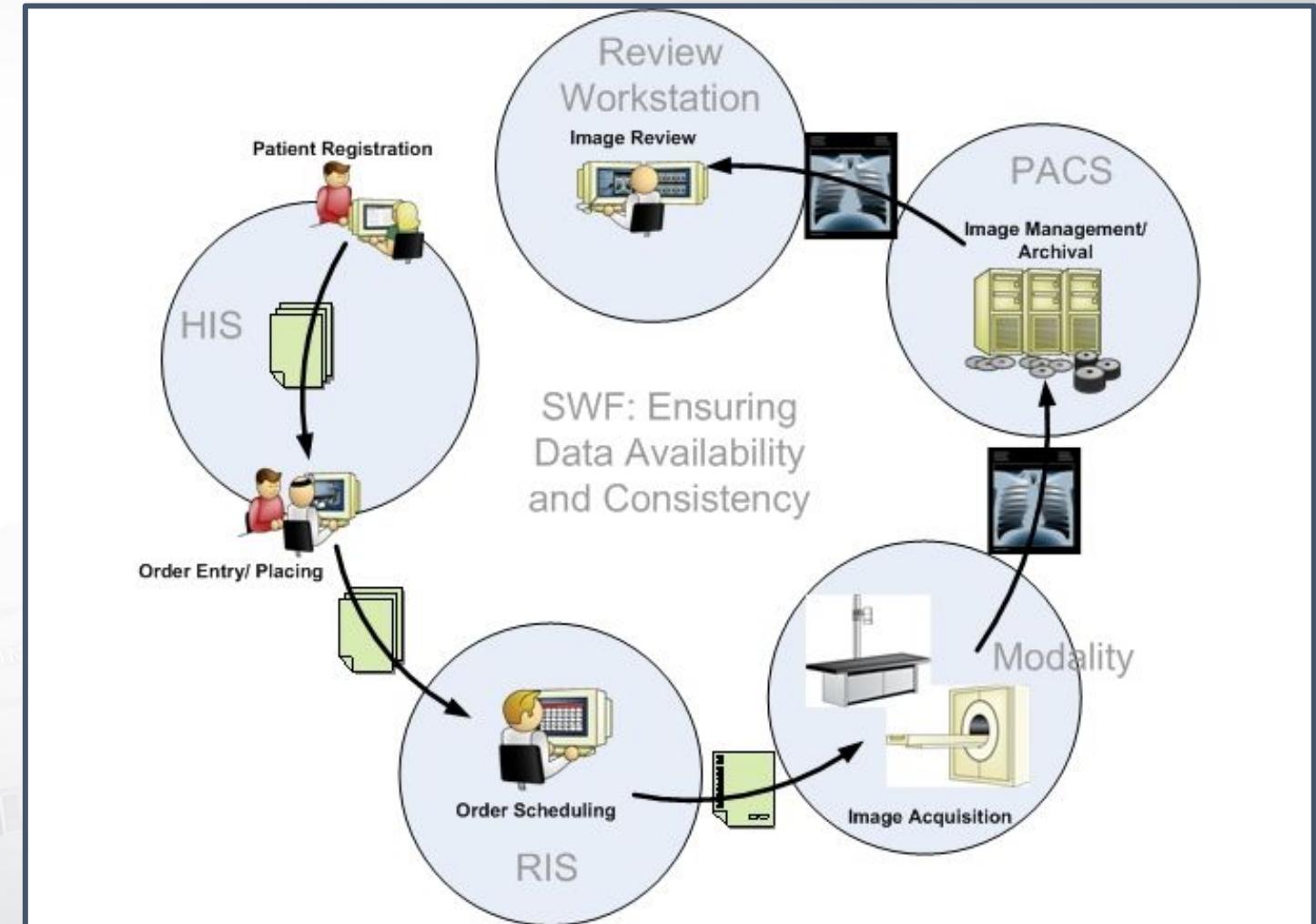


PACS

**PICTURE
ARCHIVING AND
COMMUNICATION
SYSTEM**



Scheduled Workshop



https://wiki.ihe.net/index.php/Scheduled_Workflow

Ecosistemas de Sistemas Informáticos en Salud

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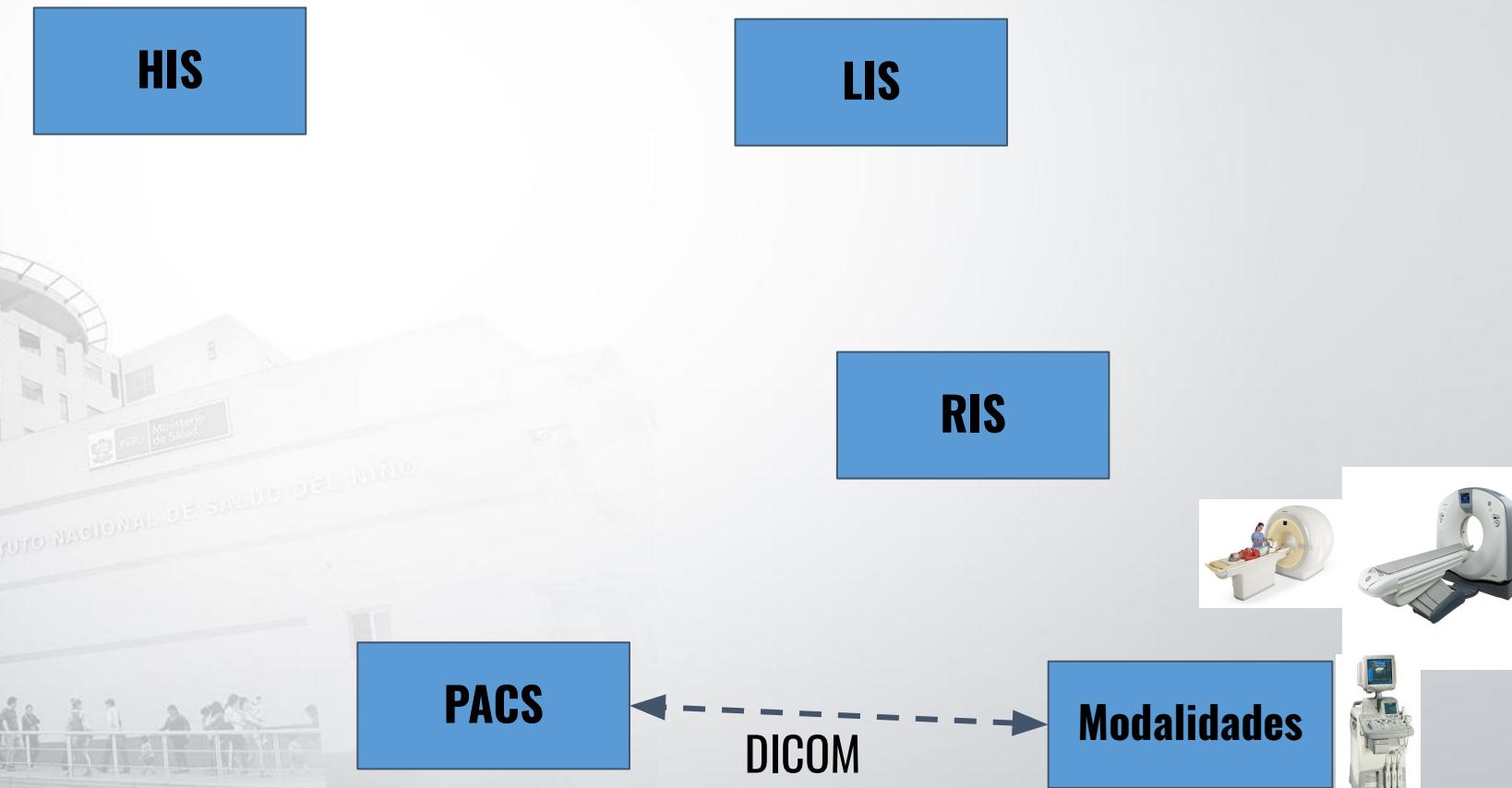
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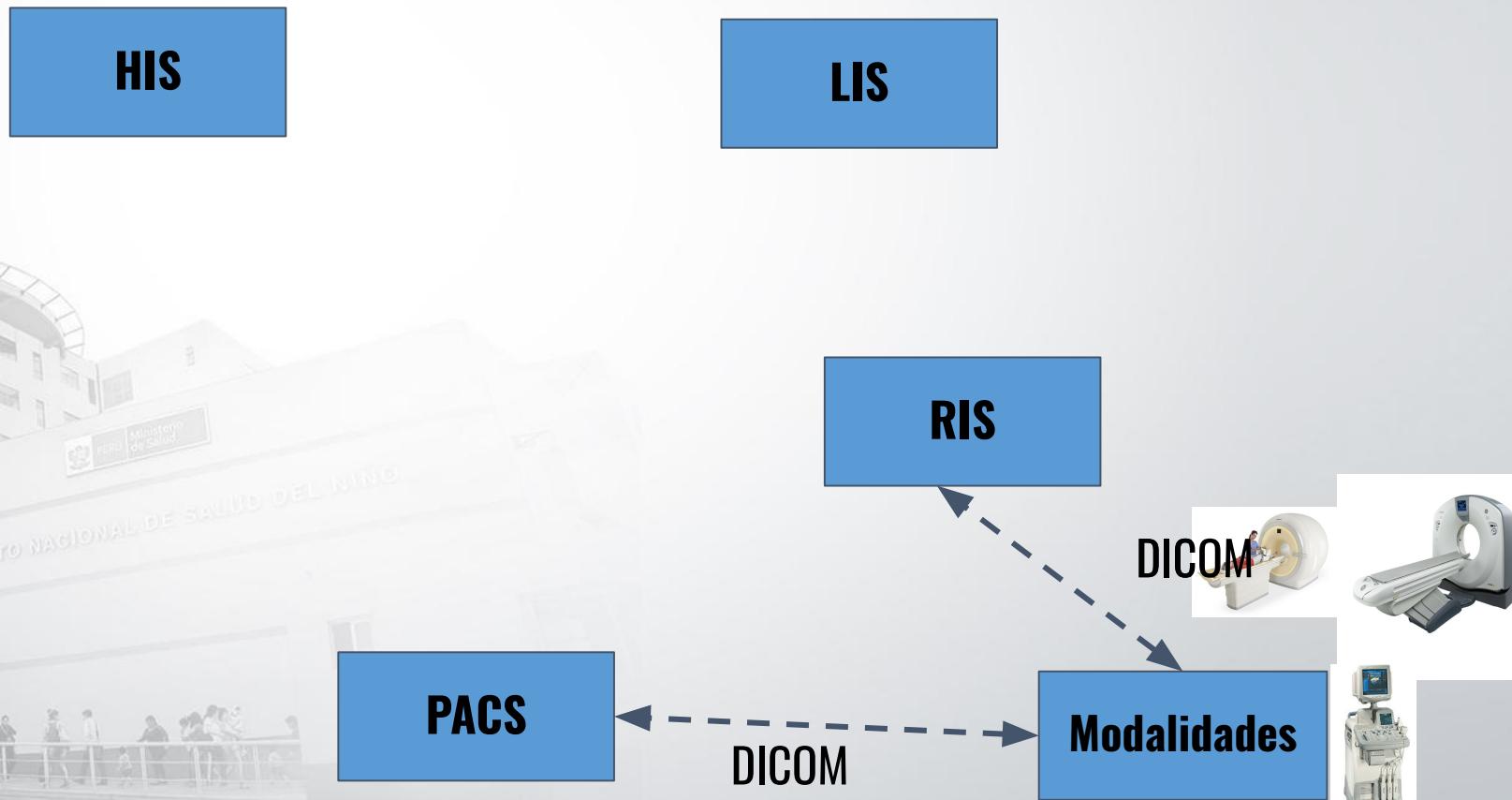
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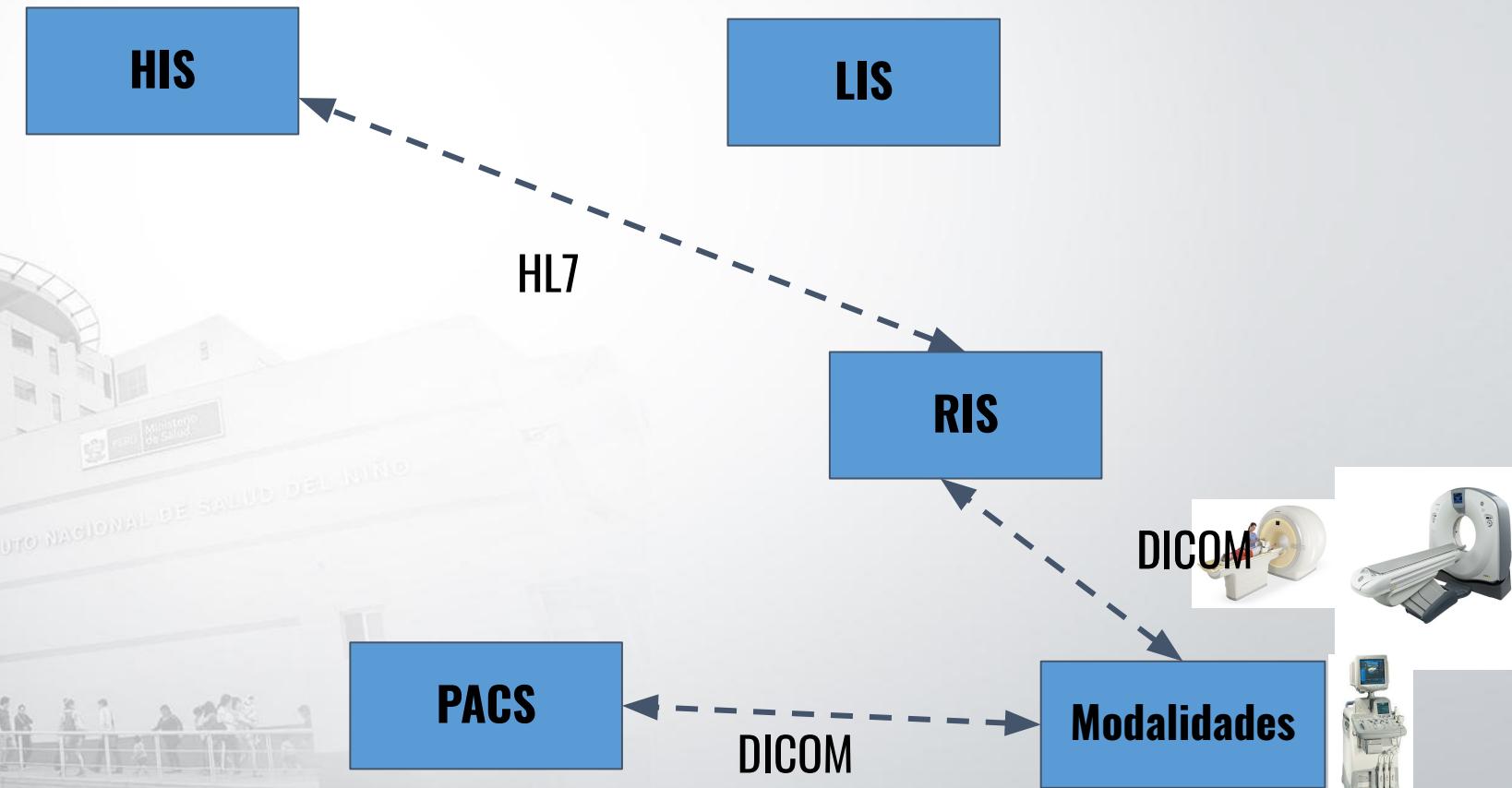
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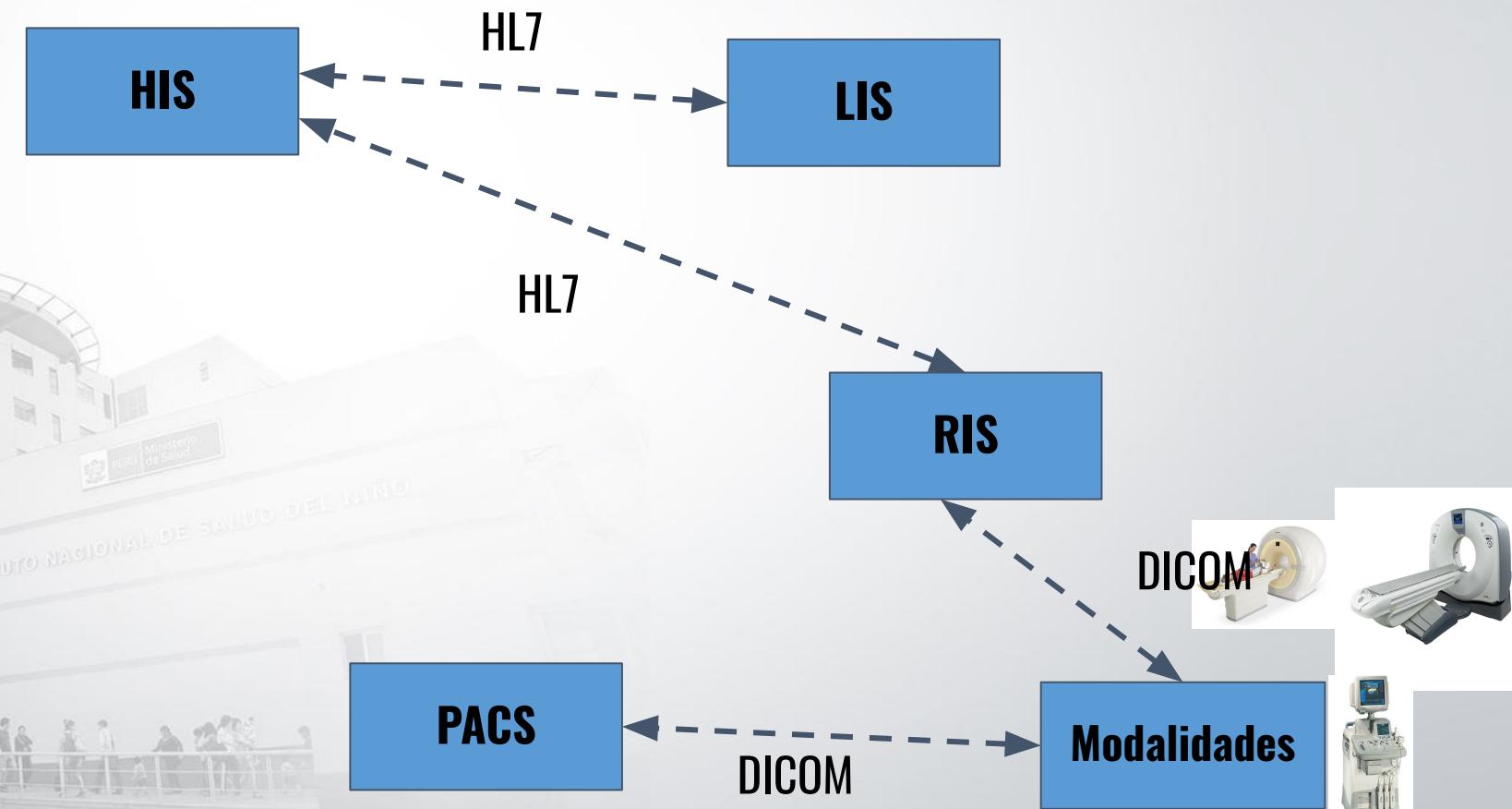
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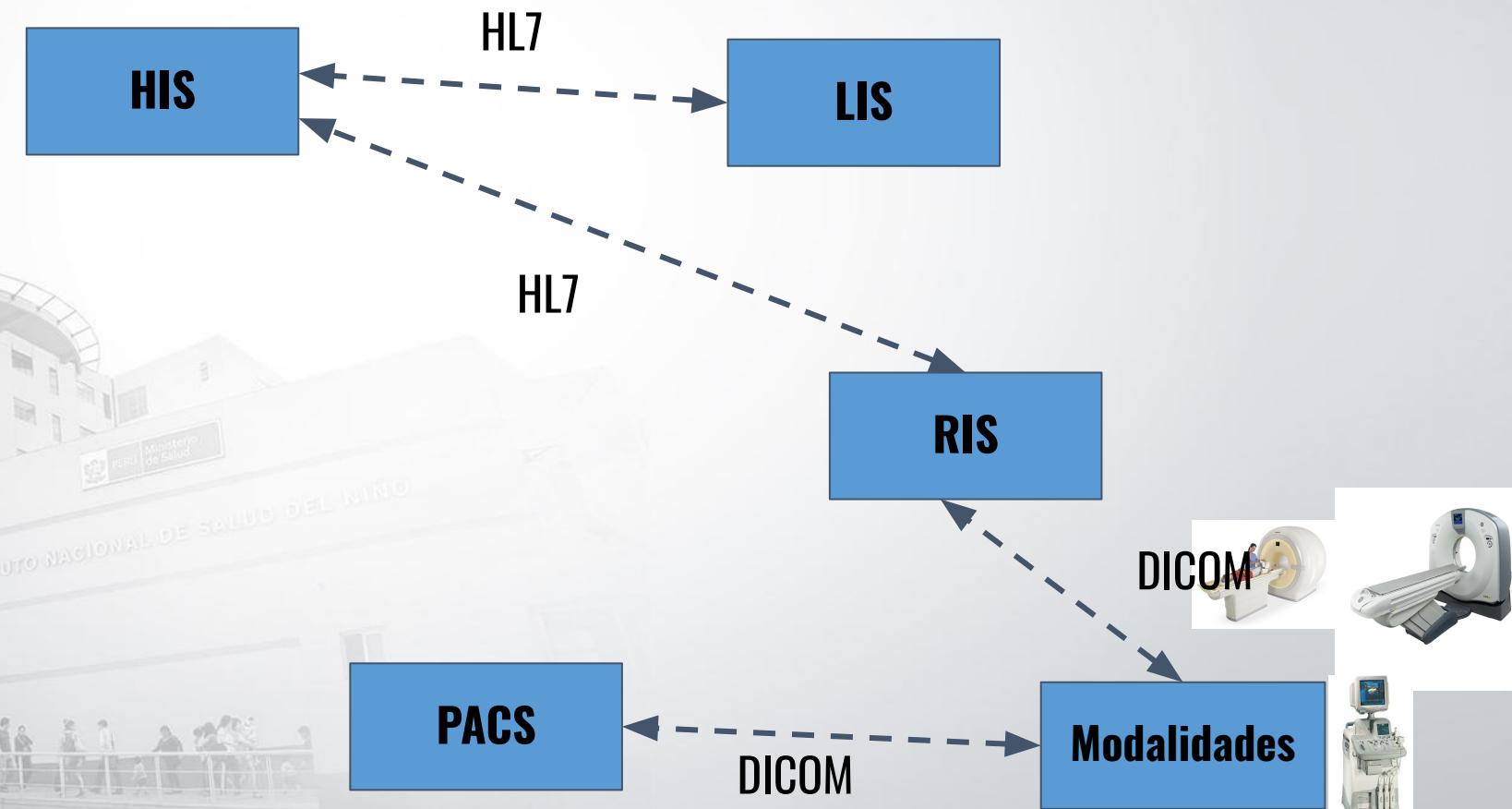
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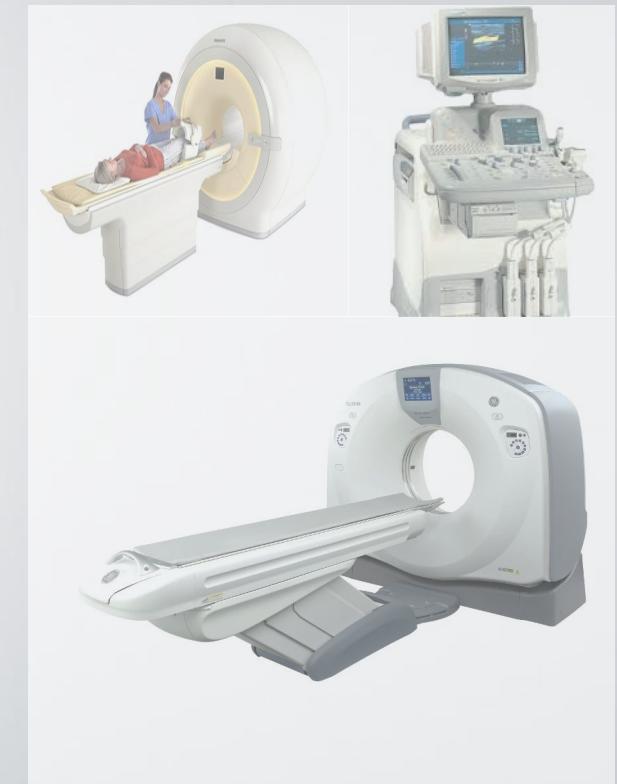
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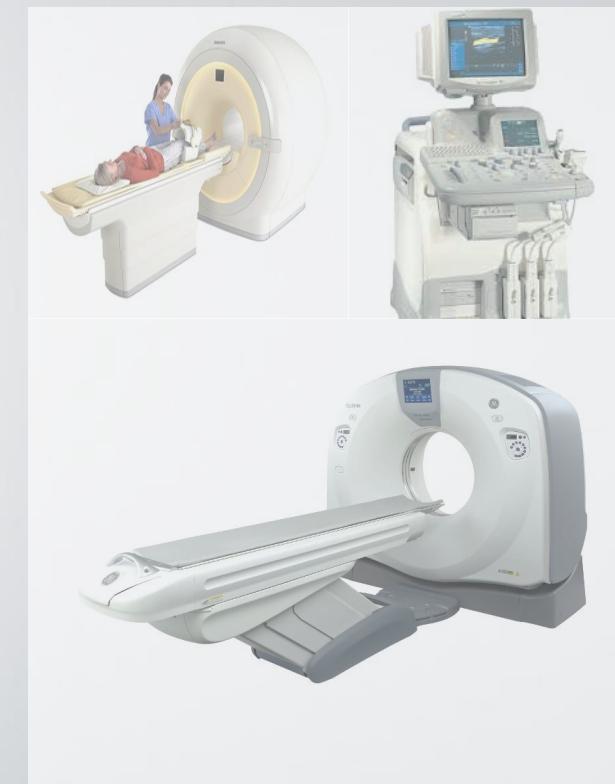
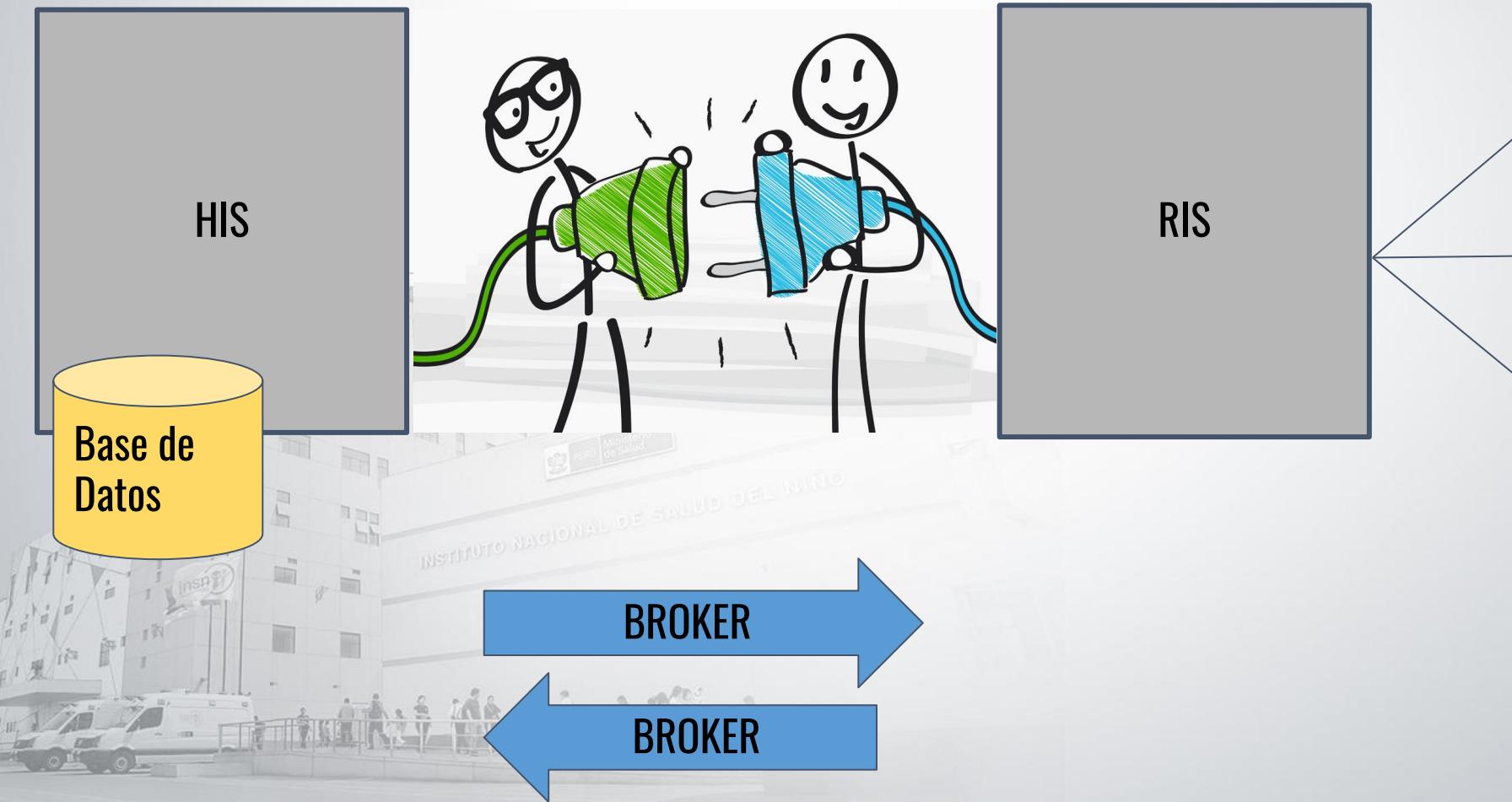
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GRACIAS...