worldusabilityday

Catch me if you can

How to fight Fraud, Waste and Abuse using Machine Learning AND Machine Teaching?

Cupid Chan

2020-11-12

Certified Section 508 Compliant

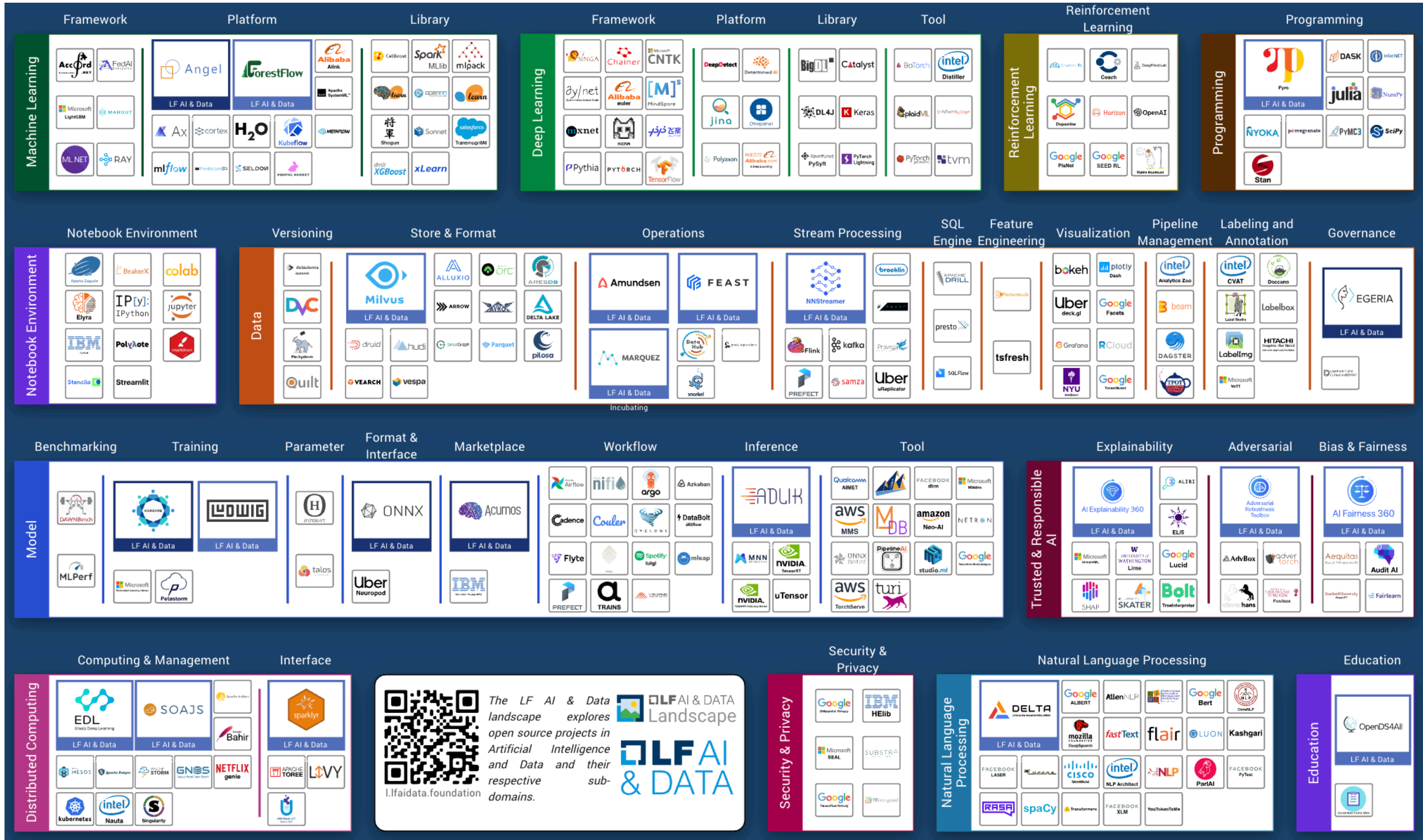
ODPi

odpi.org

+

LF AI

LF AI & DATA



Jacqueline Mars · 1st

Anthropology at Miss Hall's School

Washington D.C. Metro Area · 88 connections · Contact info

Message More...

Miss Hall's School

Highlights

16 mutual connections

You and Jacqueline both know Chung Lau, Siva Natarajan, Ph.D., and 14 others

Experience

Co-Founder

AMERICAN CANDY CO LIMITED

Sep 1982 – Sep 2001 · 19 yrs 1 mo

Education

Miss Hall's School

Anthropology

Jacqueline Mars

Active now

Jacqueline Mars · 1st

Anthropology at Miss Hall's School

TODAY

Jacqueline Mars • 6:58 PM

Hello 👋

Jacqueline Mars • 8:32 PM

Hi Cupid , Good to view your network , i am an investor ,I always honored and inspired to meet great profile and great men like you, i am hoping to see how well we can work together in future has i have just activated my LinkedIn! Jacqueline

Cupid Chan • 9:02 PM

Welcome to LinkedIn, Jacqueline! Let's keep in touch and see what can we work together in the future.

Jacqueline Mars • 10:02 PM

Absolutely

I am an investor and an anthropologist.i am from Washington DC but presently based in The plains, Virginia. i am also founders of the American candy company Mars, Incorporated.

www.mars.com

Cupid Chan • 10:13 PM

I am in a Virginian too. Nice to meet you!

Jacqueline Mars • 10:15 PM

Same here

What do you do?

Cupid Chan • 10:18 PM

I help organization to leverage the data they have using AI and Analytics.

For example, use in prevent Fraud, Waste and Abuse, predicting sales... etc.

Jacqueline Mars • 10:19 PM

Interesting

Jacqueline Mars • 10:21 PM

I would like you to share with me in exclusive about yourself and what you do in your industry, what potentials you have. And how profitable it is..as I am seeking to invest in private organizations, Government organizations and even individuals..This is why I am a business woman and rated world wide.

Cupid Chan • 10:25 PM

By "exclusive", you mean in what sense?

Jacqueline Mars • 10:26 PM

Yes, exactly

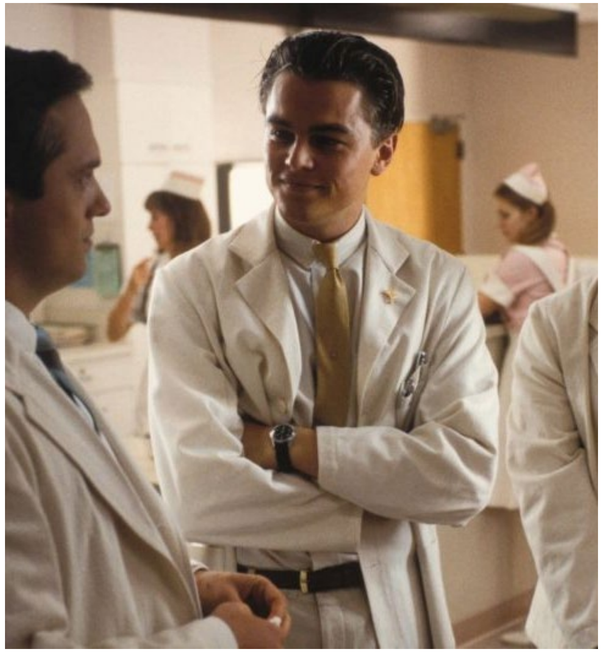
Cupid Chan • 10:29 PM

I am sorry, but exactly what?

LinkedIn Story to be continued...

10 seconds Polling Question

Have you watched the movie “Catch me if you can”?


PAN AM


How to fight **F**raud, **W**aste and **A**buse using Machine Learning AND Machine Teaching?

Presented by

Cupid Chan

Human-Centered Design
Center of Excellence

WORLD USABILITY DAY

Fraud, Waste, Abuse and Error

Fraud
Intentional Deception

Abuse
Bending the rules

Waste
Inefficiency

Error
Unintentional fault

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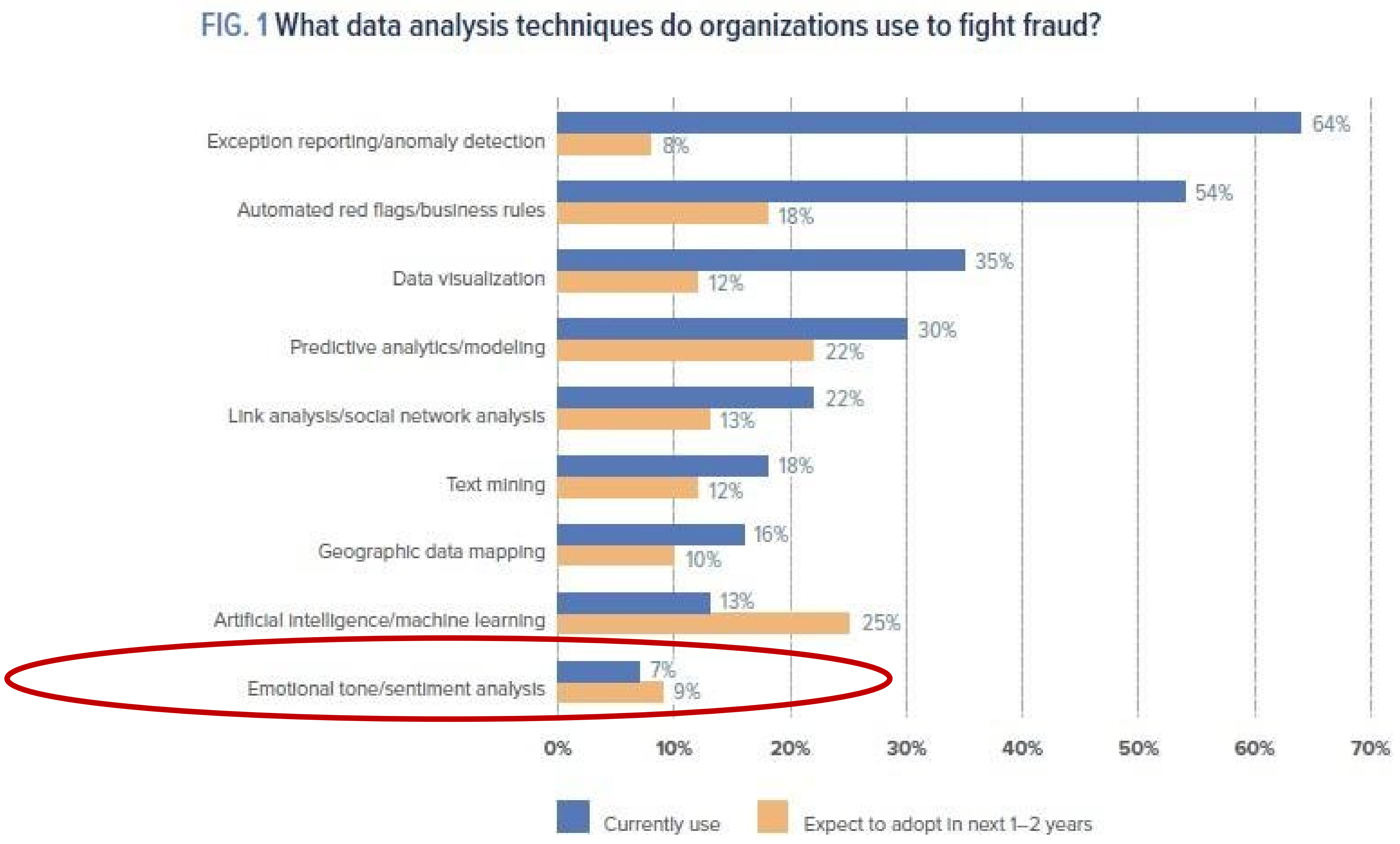

For more information about how AI Is predicting the future of online fraud detection, see the link below.
https://www.forbes.com/sites/louiscolumbus/2019/08/01/ai-is-predicting-the-future-of-online-fraud-detection/#1a19bfa374f5

10 seconds Polling Question - 1

Which of the following popular fraud costing the most?

- Credit card Fraud
- Healthcare Fraud
- Identity Fraud

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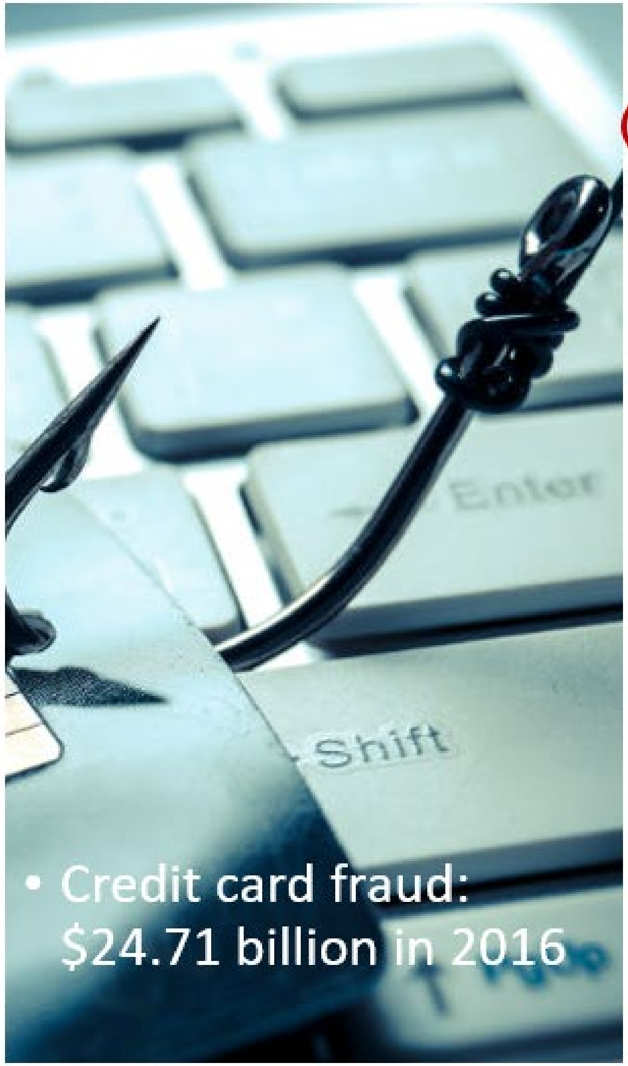
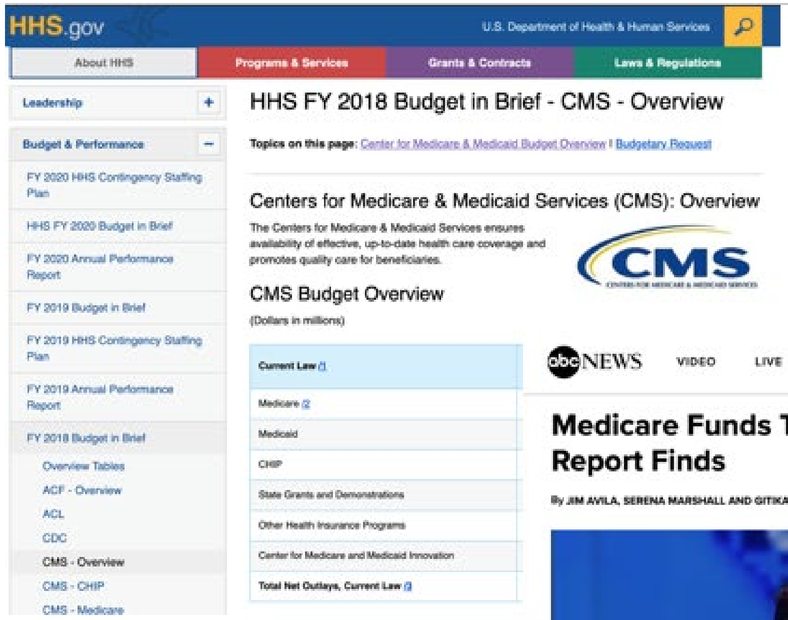
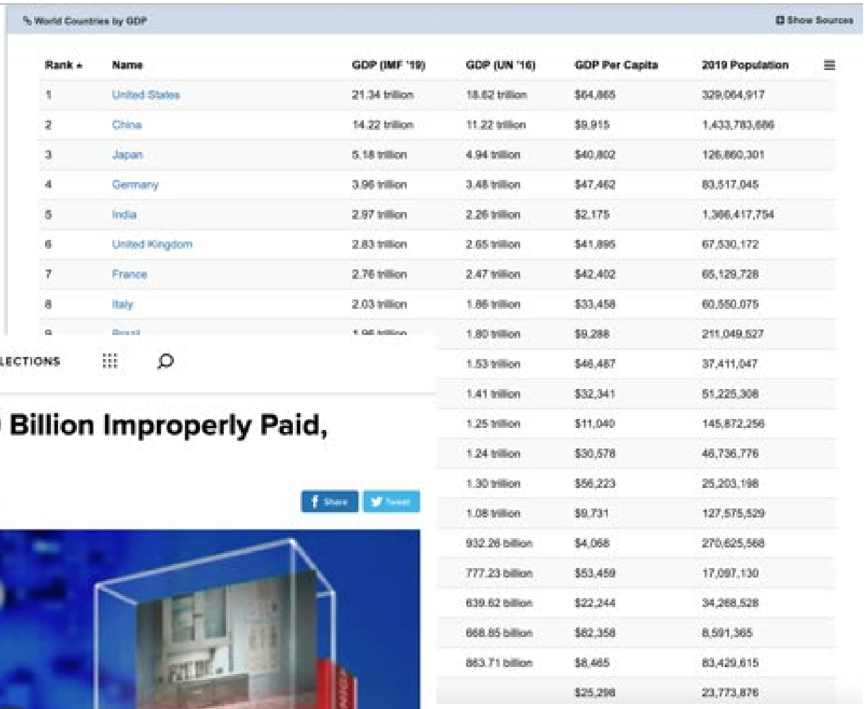
Cost of Fraud



For more information about the cost of fraud, click the links below.
https://www.bcbsm.com/health-care-fraud/fraud-statistics.html
https://losspreventionmedia.com/credit-card-fraud-news-2018-update/
https://www.javelinstrategy.com/coverage-area/2019-identity-fraud-report-fraudsters-seek-new-targets-and-victims-bear-brunt

CMS Costs of Fraud



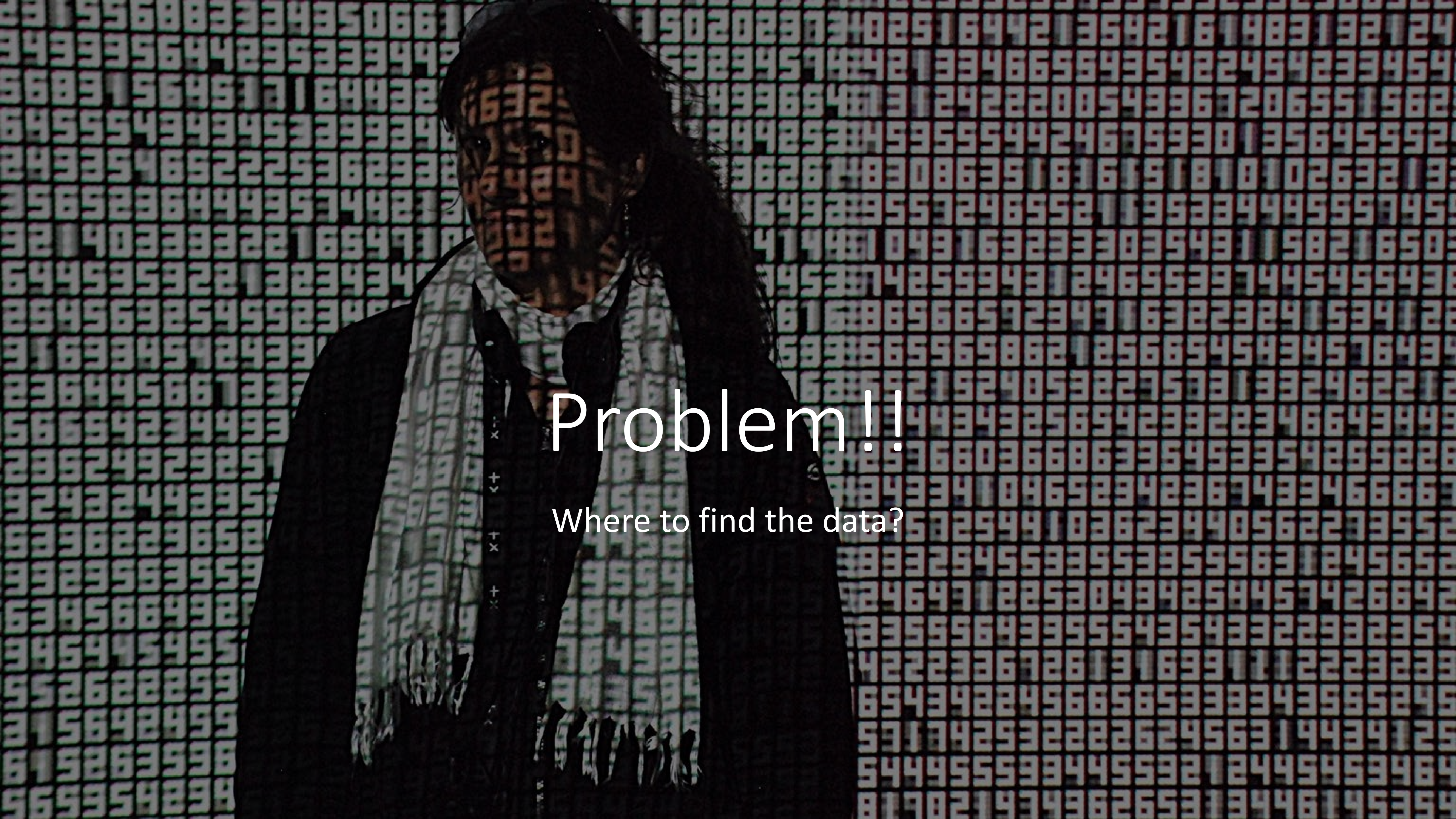

World Countries by GDP

Show Sources

Rank	Name	GDP (IMF '19)	GDP (UN '16)	GDP Per Capita	2019 Population
1	United States	21.34 trillion	18.62 trillion	$64,865	329,064,917
2	China	14.22 trillion	11.22 trillion	$9,915	1,433,783,686
3	Japan	5.18 trillion	4.94 trillion	$40,802	126,860,301
4	Germany	3.96 trillion	3.48 trillion	$47,462	83,517,045
5	India	2.97 trillion	2.26 trillion	$2,175	1,366,417,754
6	United Kingdom	2.83 trillion	2.65 trillion	$41,895	67,530,172
7	France	2.76 trillion	2.47 trillion	$42,402	65,129,728
8	Italy	2.03 trillion	1.86 trillion	$33,458	60,550,075
			1.80 trillion	$9,288	211,049,527
			1.53 trillion	$46,487	37,411,047
			1.41 trillion	$32,341	51,225,308
			1.25 trillion	$11,040	145,872,256
			1.24 trillion	$30,578	46,736,776
			1.30 trillion	$56,223	25,203,198
			1.08 trillion	$9,731	127,575,529
			932.26 billion	$4,068	270,625,568
			777.23 billion	$53,459	17,097,130
			639.62 billion	$22,244	34,268,528
			668.85 billion	$82,358	8,591,365
			863.71 billion	$8,465	83,429,615
				$25,298	23,773,876

> $1 Trillion

For more information about the costs of fraud, click the links below.
http://worldpopulationreview.com/countries/countries-by-gdp/
https://www.hhs.gov/about/budget/fy2018/budget-in-brief/cms/index.html#overview
http://abcnews.go.com/Politics/medicare-funds-totaling-60-billion-improperly-paid-report/story?id=32604330



Problem !!

Where to find the data?

Medicare Provider Utilization and Payment Data: Physician and Other Supplier

Medicare Provider Utilization and Payment Data: Physician and Other Supplier

The Physician and Other Supplier Public Use File (Physician and Other Supplier PUF) provides information on services and procedures provided to Medicare beneficiaries by physicians and other healthcare professionals. The Physician and Other Supplier PUF contains information on utilization, payment (allowed amount and Medicare payment), and submitted charges organized by National Provider Identifier (NPI), Healthcare Common Procedure Coding System (HCPCS) code, and place of service. This PUF is based on information from CMS administrative claims data for Medicare beneficiaries enrolled in the fee-for-service program. The data in the Physician and Other Supplier PUF covers calendar years 2012 through 2017 and contains 100% final-action physician/supplier Part B non-institutional line items for the Medicare fee-for-service population.

While the Physician and Other Supplier PUF has a wealth of information on payment and utilization for Medicare Part B services, the dataset has a number of limitations. Of particular importance is the fact that the data may not be representative of a physician's entire practice as it only includes information on Medicare fee-for-service beneficiaries. In addition, the data are not intended to indicate the quality of care provided and are not risk-adjusted to account for differences in underlying severity of disease of patient populations. For additional limitations, please review the methodology document available below.

- Medicare Physician and Other Supplier Data CY 2017
- Medicare Physician and Other Supplier Data CY 2016
- Medicare Physician and Other Supplier Data CY 2015
- Medicare Physician and Other Supplier Data CY 2014
- Medicare Physician and Other Supplier Data CY 2013
- Medicare Physician and Other Supplier Data CY 2012

Inquiries regarding this data can be sent to MedicareProviderData@cms.hhs.gov.

To receive email notifications, please sign up for the Medicare Provider Data GovDelivery subscription here.

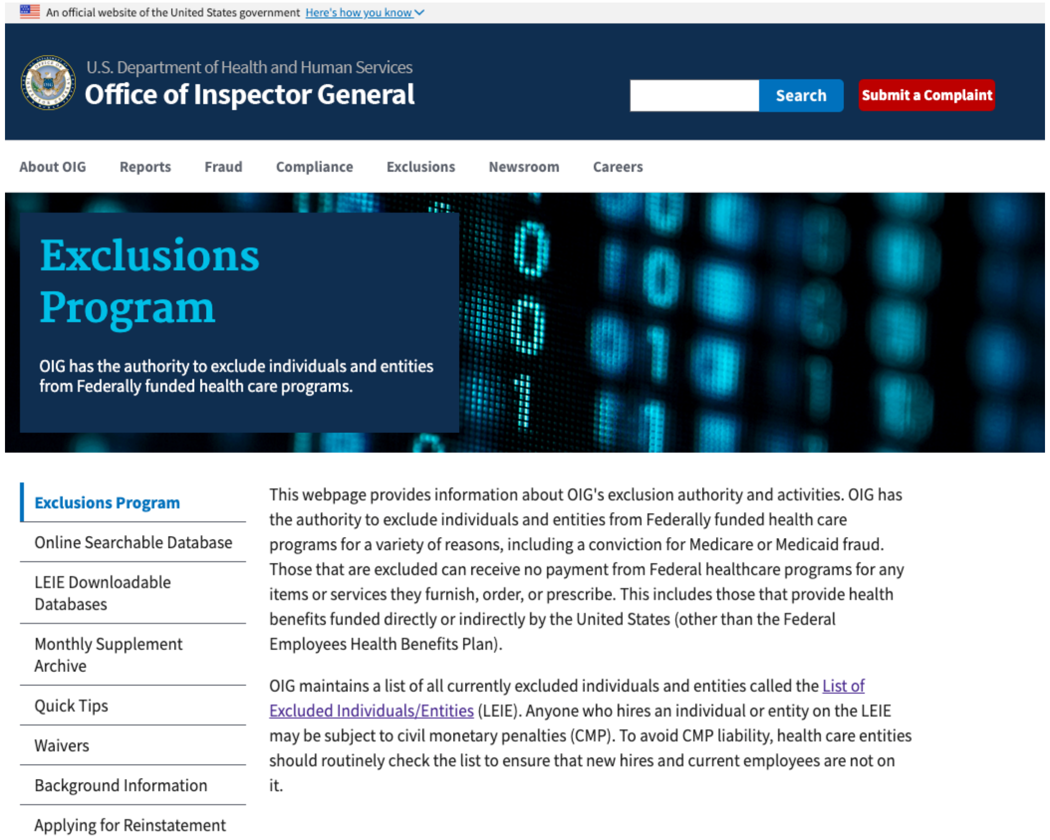
Downloads

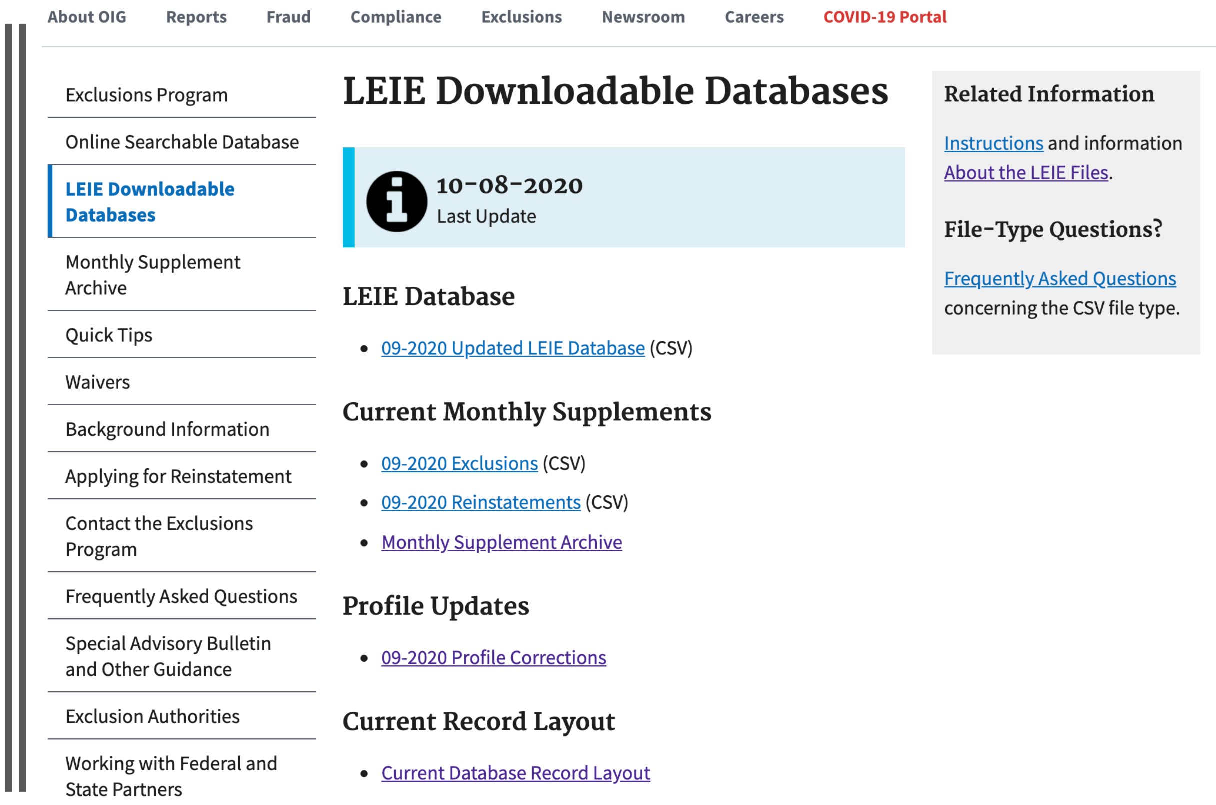
- Medicare Physician and Other Supplier PUF Methodology [PDF, 357KB]
- Medicare Physician and Other Supplier PUF Frequently Asked Questions [PDF, 135KB]

Page last Modified: 07/12/2019 10:23 AM

2012	2013	2014	2015	2016	2017
NPI	NPI	npi	npi	NPI	npi
NPPES_PROVIDER_LAST_ORG_NAME	NPPES_PROVIDER_LAST_ORG_NAME	nppes_provider_last_org_name	nppes_provider_last_org_name	NPPES_PROVIDER_LAST_ORG_NAME	nppes_provider_last_org_name
NPPES_PROVIDER_FIRST_NAME	NPPES_PROVIDER_FIRST_NAME	nppes_provider_first_name	nppes_provider_first_name	NPPES_PROVIDER_FIRST_NAME	nppes_provider_first_name
NPPES_PROVIDER_MI	NPPES_PROVIDER_MI	nppes_provider_mi	nppes_provider_mi	NPPES_PROVIDER_MI	nppes_provider_mi
NPPES_CREDENTIALS	NPPES_CREDENTIALS	nppes_credentials	nppes_credentials	NPPES_CREDENTIALS	nppes_credentials
NPPES_PROVIDER_GENDER	NPPES_PROVIDER_GENDER	nppes_provider_gender	nppes_provider_gender	NPPES_PROVIDER_GENDER	nppes_provider_gender
NPPES_ENTITY_CODE	NPPES_ENTITY_CODE	nppes_entity_code	nppes_entity_code	NPPES_ENTITY_CODE	nppes_entity_code
NPPES_PROVIDER_STREET1	NPPES_PROVIDER_STREET1	nppes_provider_street1	nppes_provider_street1	NPPES_PROVIDER_STREET1	nppes_provider_street1
NPPES_PROVIDER_STREET2	NPPES_PROVIDER_STREET2	nppes_provider_street2	nppes_provider_street2	NPPES_PROVIDER_STREET2	nppes_provider_street2
NPPES_PROVIDER_CITY	NPPES_PROVIDER_CITY	nppes_provider_city	nppes_provider_city	NPPES_PROVIDER_CITY	nppes_provider_city
NPPES_PROVIDER_ZIP	NPPES_PROVIDER_ZIP	nppes_provider_zip	nppes_provider_zip	NPPES_PROVIDER_ZIP	nppes_provider_zip
NPPES_PROVIDER_STATE	NPPES_PROVIDER_STATE	nppes_provider_state	nppes_provider_state	NPPES_PROVIDER_STATE	nppes_provider_state
NPPES_PROVIDER_COUNTRY	NPPES_PROVIDER_COUNTRY	nppes_provider_country	nppes_provider_country	NPPES_PROVIDER_COUNTRY	nppes_provider_country
PROVIDER_TYPE	PROVIDER_TYPE	provider_type	provider_type	PROVIDER_TYPE	provider_type
MEDICARE_PARTICIPATION_INDICATOR	MEDICARE_PARTICIPATION_INDICATOR	medicare_participation_indicator	medicare_participation_indicator	MEDICARE_PARTICIPATION_INDICATOR	medicare_participation_indicator
PLACE_OF_SERVICE	PLACE_OF_SERVICE	place_of_service	place_of_service	PLACE_OF_SERVICE	place_of_service
HCPCS_CODE	HCPCS_CODE	hcpcs_code	hcpcs_code	HCPCS_CODE	hcpcs_code
HCPCS_DESCRIPTION	HCPCS_DESCRIPTION	hcpcs_description	hcpcs_description	HCPCS_DESCRIPTION	hcpcs_description
HCPCS_DRUG_INDICATOR	HCPCS_DRUG_INDICATOR	hcpcs_drug_indicator	hcpcs_drug_indicator	HCPCS_DRUG_INDICATOR	hcpcs_drug_indicator
LINE_SRVC_CNT	LINE_SRVC_CNT	line_srvc_cnt	line_srvc_cnt	LINE_SRVC_CNT	line_srvc_cnt
BENE_UNIQUE_CNT	BENE_UNIQUE_CNT	bene_unique_cnt	bene_unique_cnt	BENE_UNIQUE_CNT	bene_unique_cnt
BENE_DAY_SRVC_CNT	BENE_DAY_SRVC_CNT	bene_day_srvc_cnt	bene_day_srvc_cnt	BENE_DAY_SRVC_CNT	bene_day_srvc_cnt
AVERAGE_MEDICARE_ALLOWED_AMT	AVERAGE_MEDICARE_ALLOWED_AMT	average_Medicare_allowed_amt	average_Medicare_allowed_amt	AVERAGE_MEDICARE_ALLOWED_AMT	average_Medicare_allowed_amt
STDEV_MEDICARE_ALLOWED_AMT	STDEV_MEDICARE_ALLOWED_AMT	average_submitted_chrg_amt	average_submitted_chrg_amt	AVERAGE_SUBMITTED_CHRG_AMT	average_submitted_chrg_amt
AVERAGE_SUBMITTED_CHRG_AMT	AVERAGE_SUBMITTED_CHRG_AMT	average_Medicare_payment_amt	average_Medicare_payment_amt	AVERAGE_MEDICARE_PAYMENT_AMT	average_Medicare_payment_amt
STDEV_SUBMITTED_CHRG_AMT	STDEV_SUBMITTED_CHRG_AMT	average_Medicare_standard_amt	average_Medicare_standard_amt	AVERAGE_MEDICARE_STANDARD_AMT	average_Medicare_standard_amt
AVERAGE_MEDICARE_PAYMENT_AMT	AVERAGE_MEDICARE_PAYMENT_AMT				
STDEV_MEDICARE_PAYMENT_AMT	STDEV_MEDICARE_PAYMENT_AMT				

List of Excluded Individuals and Entities (LEIE)





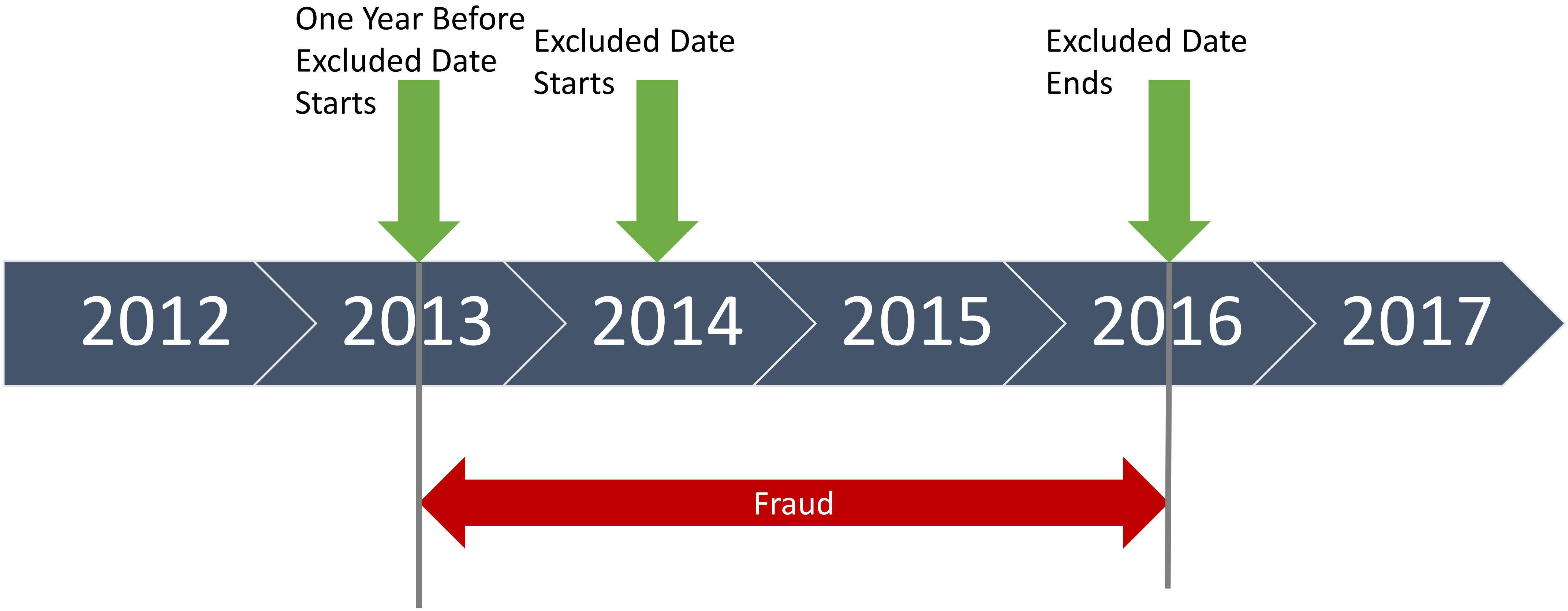
- LASTNAME
- FIRSTNAME
- MIDNAME
- BUSNAME
- GENERAL
- SPECIALTY
- UPIN
- NPI
- DOB
- ADDRESS
- CITY
- STATE
- ZIP
- EXCLTYPE
- EXCLDATE
- REINDATE
- WAIVERDATE
- WVRSTATE

Mandatory Exclusions

Social Security Act	42 USC §	Amendment
1128(a)(1)	1320a-7(a)(1)	Conviction of program-related crimes. Minimum Period: 5 years
1128(a)(2)	1320a-7(a)(2)	Conviction relating to patient abuse or neglect. Minimum Period: 5 years
1128(a)(3)	1320a-7(a)(3)	Felony conviction relating to health care fraud. Minimum Period: 5 years
1128(a)(4)	1320a-7(a)(4)	Felony conviction relating to controlled substance. Minimum Period: 5 years
1128(c)(3)(G)(i)	1320a-7(c)(3)(G)(i)	Conviction of second mandatory exclusion offense. Minimum Period: 10 years
1128(c)(3)(G)(ii)	1320a-7(c)(3)(G)(ii)	Conviction of third or more mandatory exclusion offenses. Permanent Exclusion

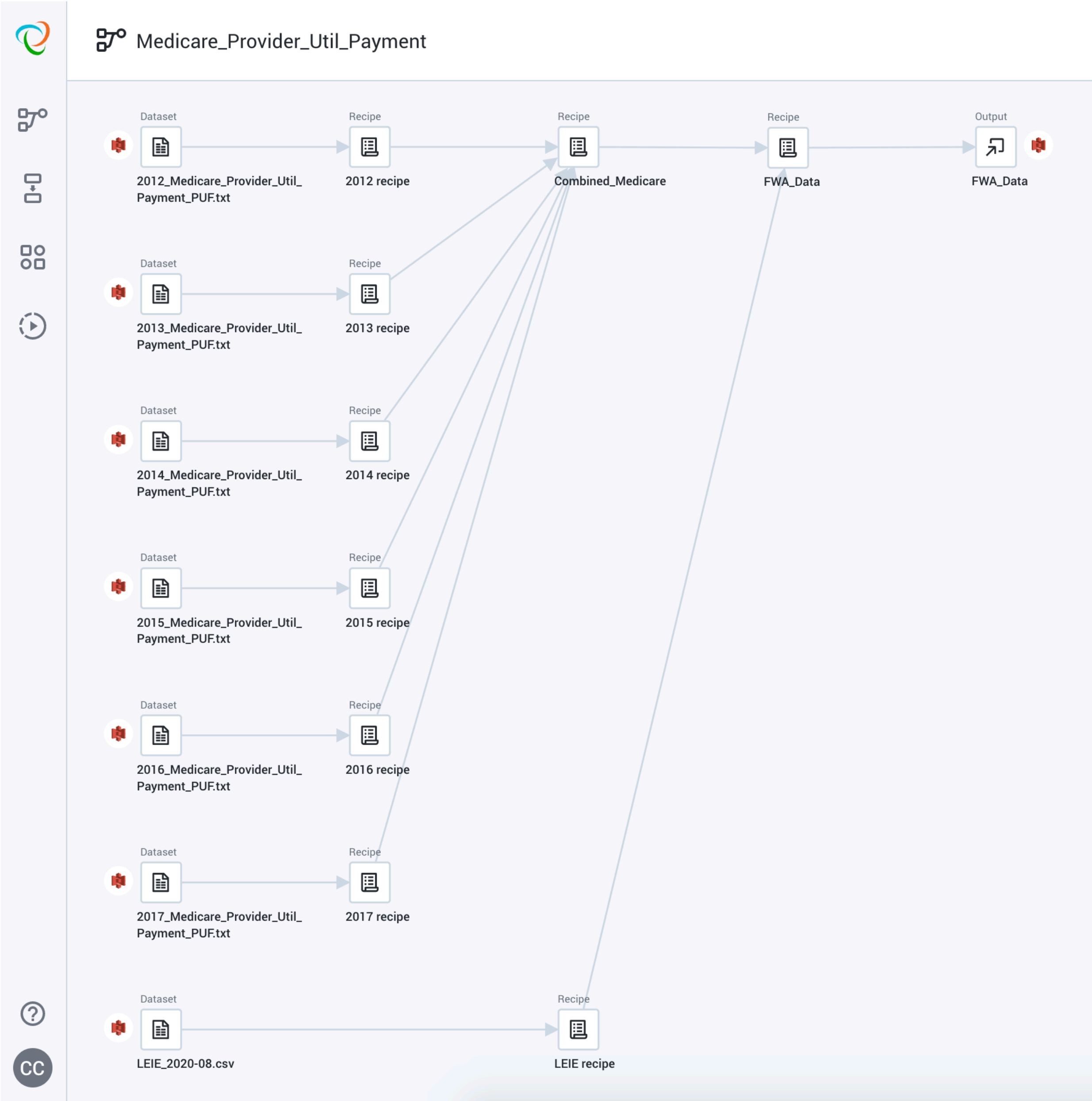
See [Office of Inspector General Exclusion Authorities](https://oig.hhs.gov/exclusions/authorities.asp) at https://oig.hhs.gov/exclusions/authorities.asp

Define what is fraud based on the data set



All HCPCS within the period are considered fraud for the NPI

Overall data ingestion flow



Final data set structure

provider_type	Provider's specialty, e.g. Internal Medicine, Dermatology
nppes_provider_gender	Provider Gender
hcpcs_code	Procedure or Service performed by the provider
line_srvc_cnt	Number of procedures or services the provider performed
bene_unique_cnt	Number of distinct Medicare beneficiaries receiving the service/procedure
bene_day_srvc_cnt	Number of distinct Medicare beneficiaries per day by the provider
average_submitted_chrg_amt	Average charge the provider submitted for the service or procedure
average_medicare_payment_amt	Average payment made to a provider per claim for the service
fraud	Fraud label based on the logic described before

Let’s predict using Machine Learning!

Based on my rich experience in AI 😎, I can build a model guaranteed with 99.9% accuracy within 10 seconds!

EVERYTHING

Is <u>NOT</u> Fraud

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Confusion Matrix

- Total: 54,337,938
- Normal: 54,333,245
- Fraud: 4,693 (0.0086%)

		Predicted Class		
		Positive	Negative	
Actual Class	Positive	True Positive (TP)	False Positive (FN)	Sensitivity/Recall $\frac{TP}{TP+FN}$
	Negative	False Negative (FP)	True Negative (TN)	Specificity $\frac{TN}{TN+FP}$
		Precision $\frac{TP}{TP+FP}$	Negative Predictive Value $\frac{TN}{TN+FN}$	Accuracy $\frac{TP+TN}{TP+TN+FP+FN}$

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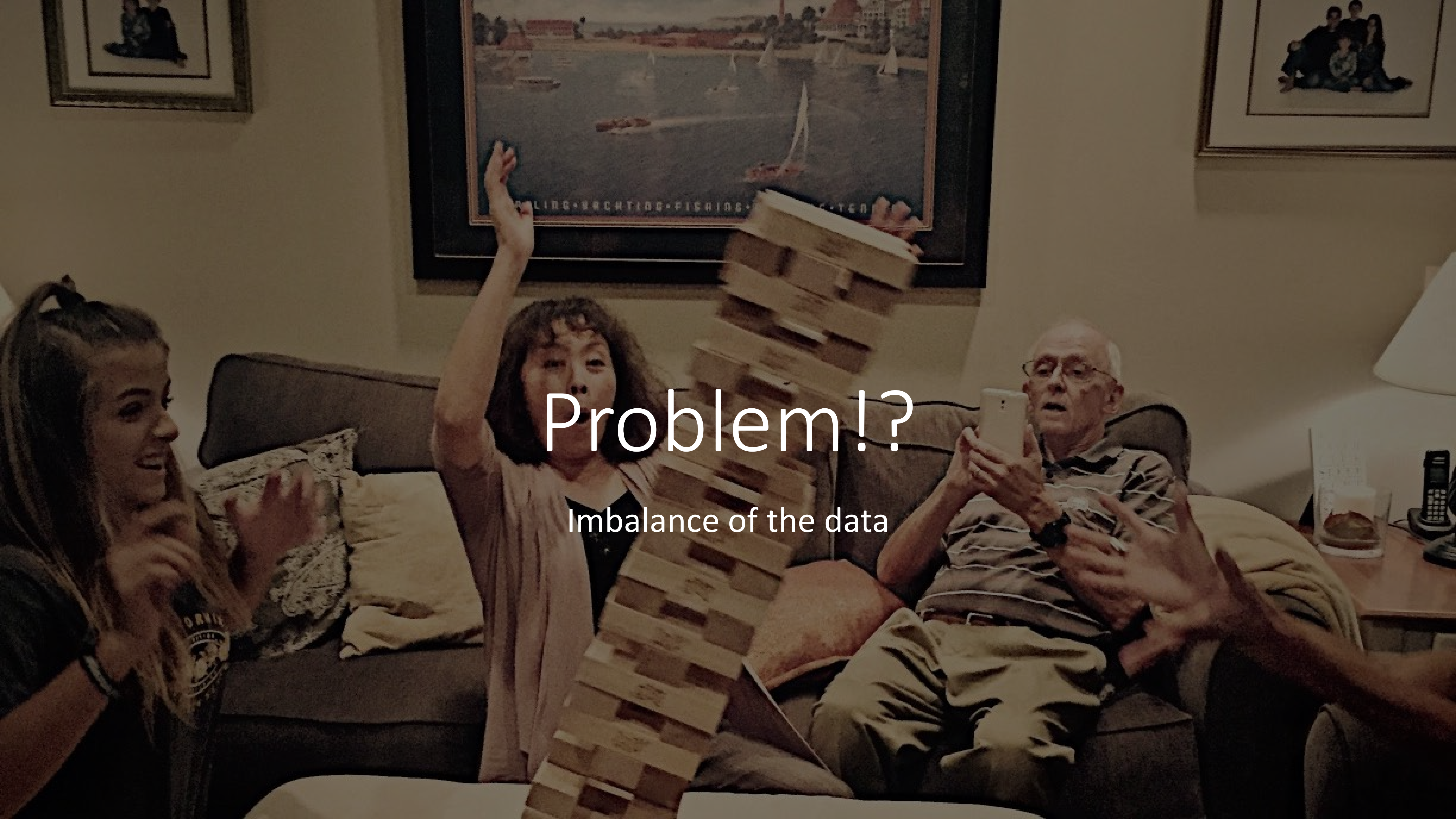


Problem!?

Imbalance of the data

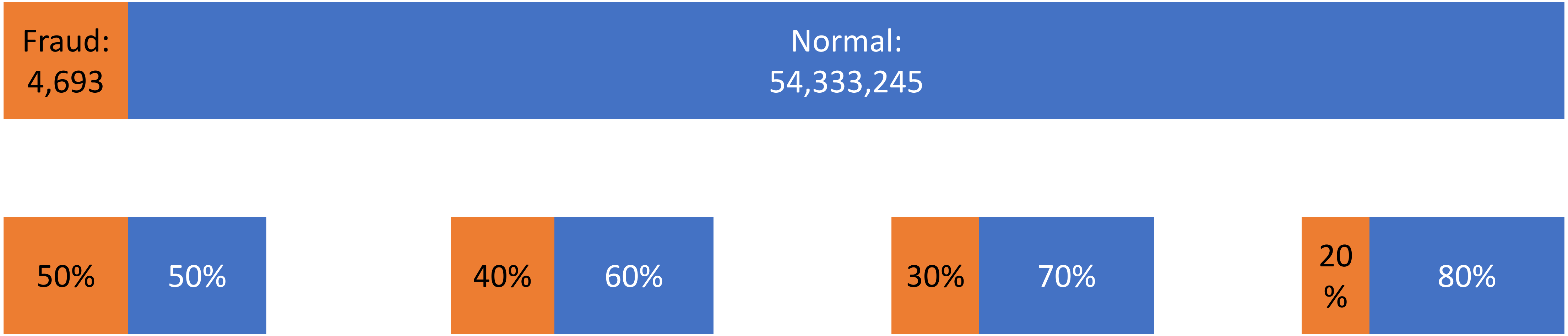
Data Discrimination – Minority Class

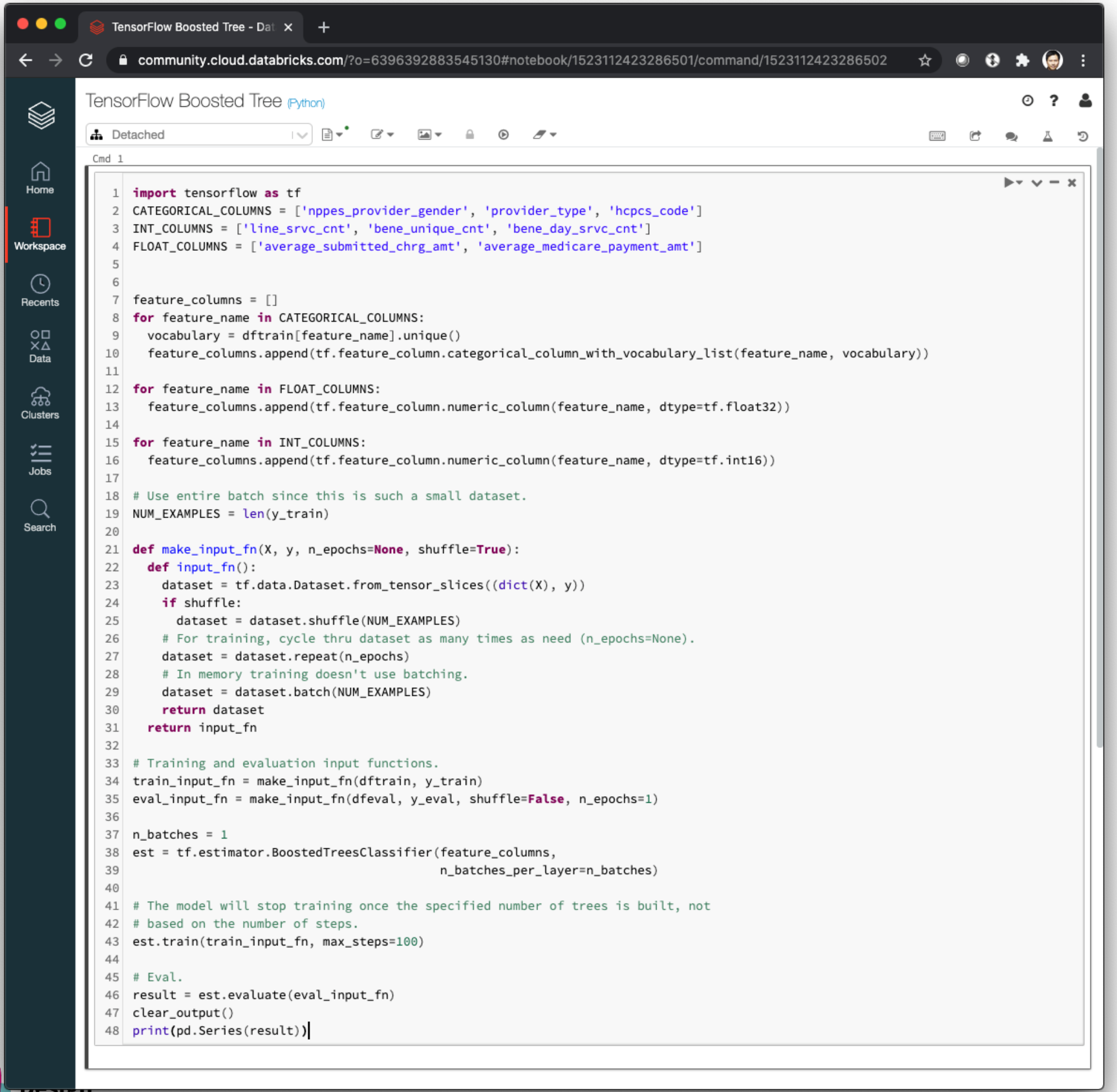
- Credit Card Fraud
- Manufacturing Defect
- Rare Disease Diagnosis
- Natural Disasters

Potential Solution for Class Imbalance

- Decreasing Majority
  - Random Under Sampling (RUS)
- Increasing Minority
  - Random Over Sampling
    - Replicate Minority Observation
    - Synthetic Minority Oversampling Technique

Random Under Sampling (RUS)






```python
import tensorflow as tf
CATEGORICAL_COLUMNS = ['nppes_provider_gender', 'provider_type', 'hcpcs_code']
INT_COLUMNS = ['line_srvc_cnt', 'bene_unique_cnt', 'bene_day_srvc_cnt']
FLOAT_COLUMNS = ['average_submitted_chrg_amt', 'average_medicare_payment_amt']


feature_columns = []
for feature_name in CATEGORICAL_COLUMNS:
  vocabulary = dftrain[feature_name].unique()
  feature_columns.append(tf.feature_column.categorical_column_with_vocabulary_list(feature_name, vocabulary))

for feature_name in FLOAT_COLUMNS:
  feature_columns.append(tf.feature_column.numeric_column(feature_name, dtype=tf.float32))

for feature_name in INT_COLUMNS:
  feature_columns.append(tf.feature_column.numeric_column(feature_name, dtype=tf.int16))

# Use entire batch since this is such a small dataset.
NUM_EXAMPLES = len(y_train)

def make_input_fn(X, y, n_epochs=None, shuffle=True):
  def input_fn():
    dataset = tf.data.Dataset.from_tensor_slices((dict(X), y))
    if shuffle:
      dataset = dataset.shuffle(NUM_EXAMPLES)
    # For training, cycle thru dataset as many times as need (n_epochs=None).
    dataset = dataset.repeat(n_epochs)
    # In memory training doesn't use batching.
    dataset = dataset.batch(NUM_EXAMPLES)
    return dataset
  return input_fn

# Training and evaluation input functions.
train_input_fn = make_input_fn(dftrain, y_train)
eval_input_fn = make_input_fn(dfeval, y_eval, shuffle=False, n_epochs=1)

n_batches = 1
est = tf.estimator.BoostedTreesClassifier(feature_columns,
                                          n_batches_per_layer=n_batches)

# The model will stop training once the specified number of trees is built, not
# based on the number of steps.
est.train(train_input_fn, max_steps=100)

# Eval.
result = est.evaluate(eval_input_fn)
clear_output()
print(pd.Series(result))
```

Using 50:50 Class Distribution

TensorFlow Boosted Tree Classifier

Accuracy: 0.760789

Precision: 0.706313

Recall: 0.857778

AUC: 0.845611

Potential Improvement

- Add back Geographical information to the data set in analysis
- Add beneficiary data to form a graph analysis. Right now we only analyze from Provide side
- More granular e.g. by type
- Add more metrics (Medicare Standard Amount, Medicare Allowed Amount)
- A lot of missing NPI in LEIE. looking up missing NPI numbers in the National Plan and Provider Enumeration System (NPPES) registry

Even with those improvements, there are still limitations

- Tagged data not always be available
- Not good for emerging anomalies with entirely new and more sophisticated forms

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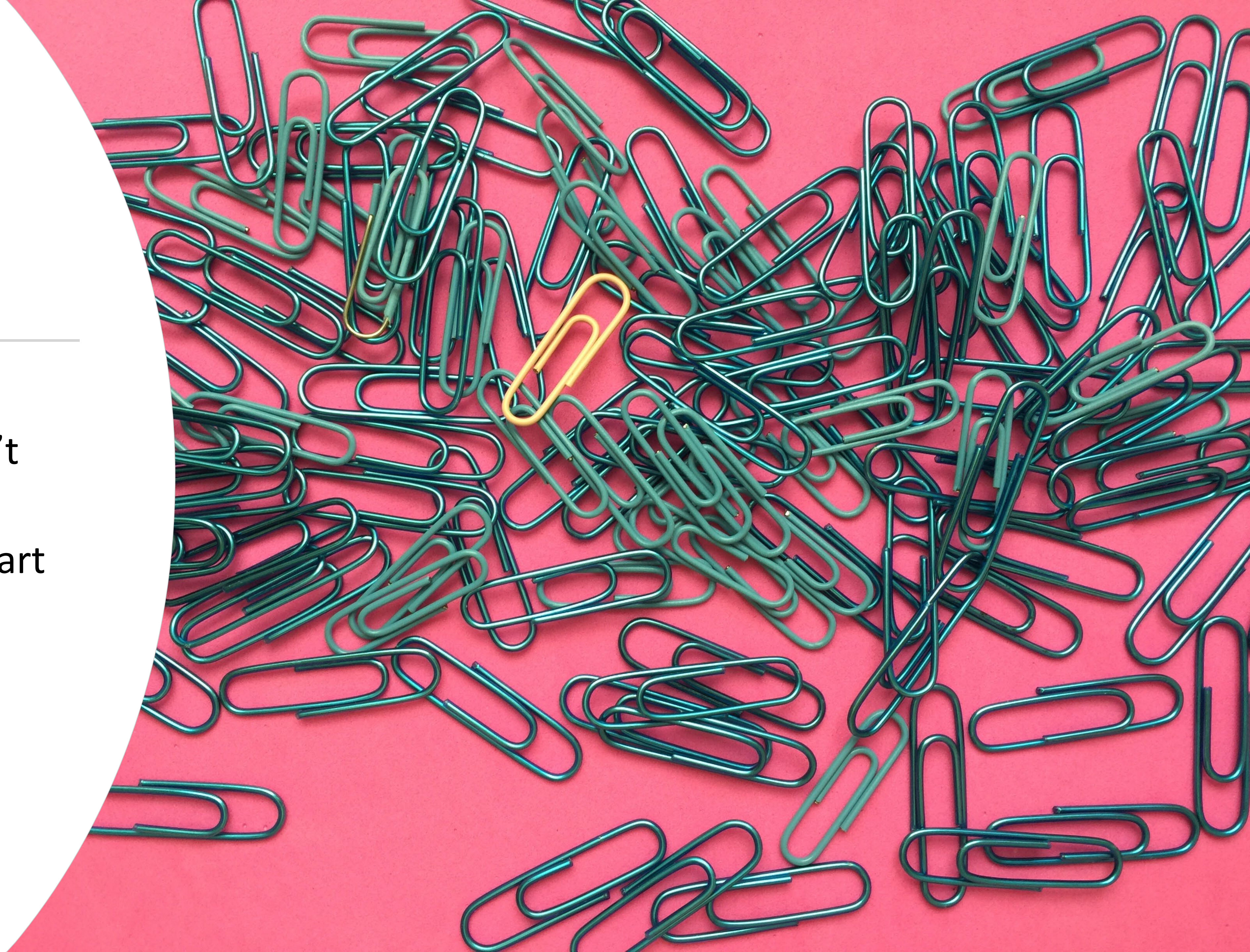
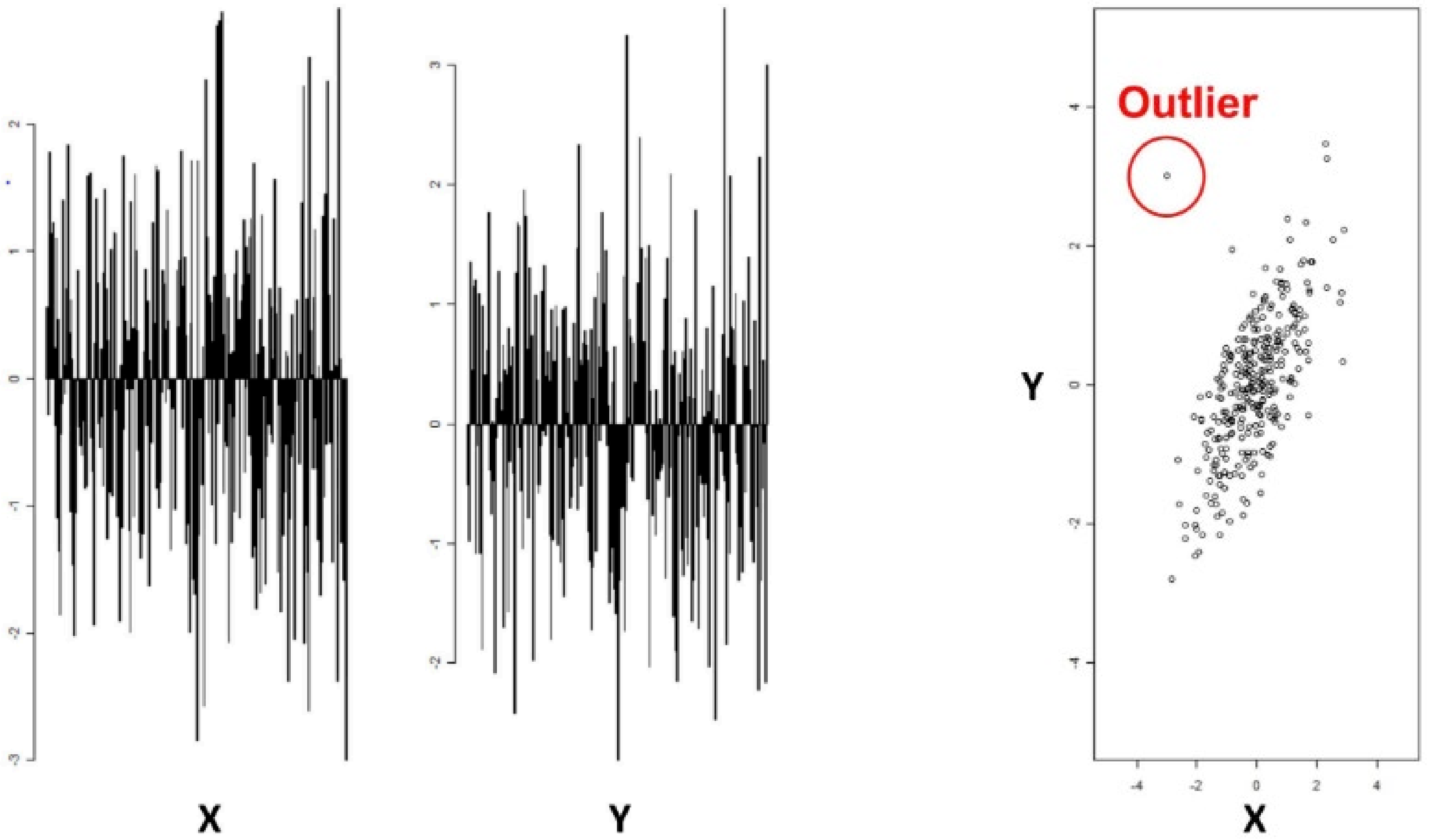
Unsupervised Learning

- Good for detecting Outlier, but it doesn’t mean that is Fraud.
- It provides hint to start finding Fraud.

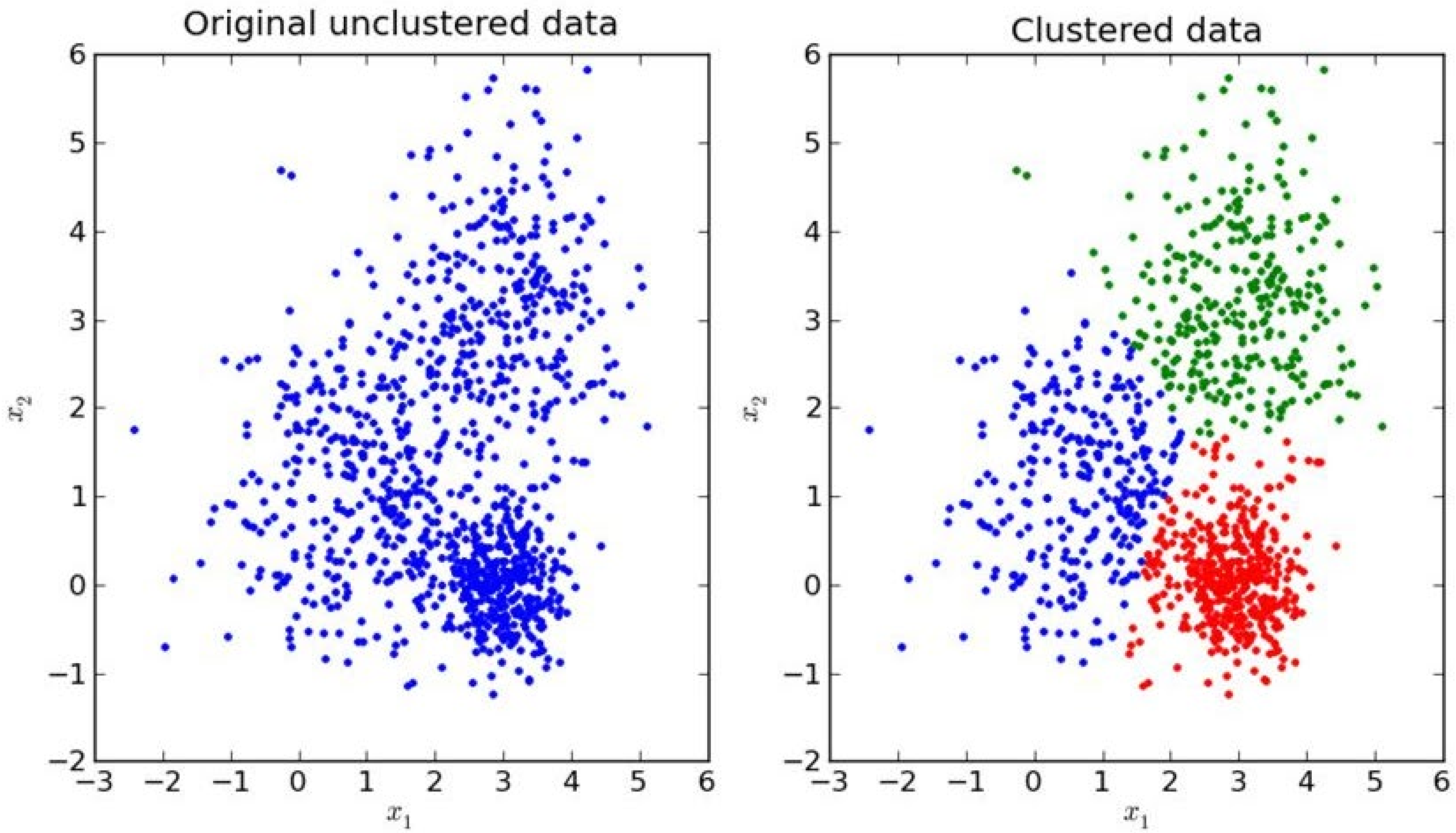


Where is the Outlier?



https://miro.medium.com/max/1944/1*BaOiTGWAoFi-3_-E-rJGdg.jpeg

Unsupervised Clustering



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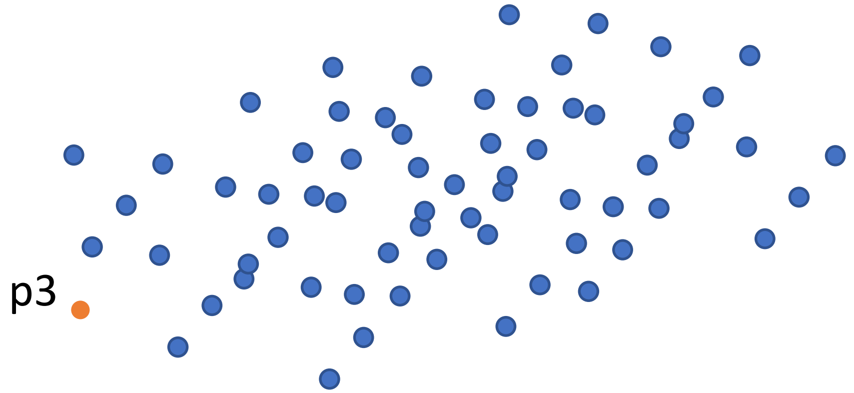
http://www.frankichamaki.com/data-driven-market-segmentation-more-effective-marketing-to-segments-using-ai/

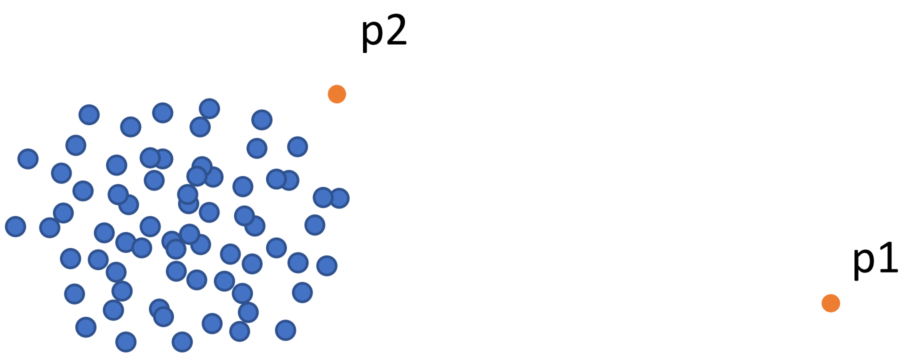
https://www.youtube.com/watch?v=BorcaCtjmog&t=4s

10 seconds Polling Question: Which point is considered outlier?

Nearest Neighbor Approach

- By distance
- Having the largest distance away from closest points
- Only p1 is considered outlier





Density based Approach

- By density
- Having the lowest density among closest points
- Both p1 and p2 are considered outlier

10 seconds Polling Question - 3

You must know her for this 3rd approach

Who is she?

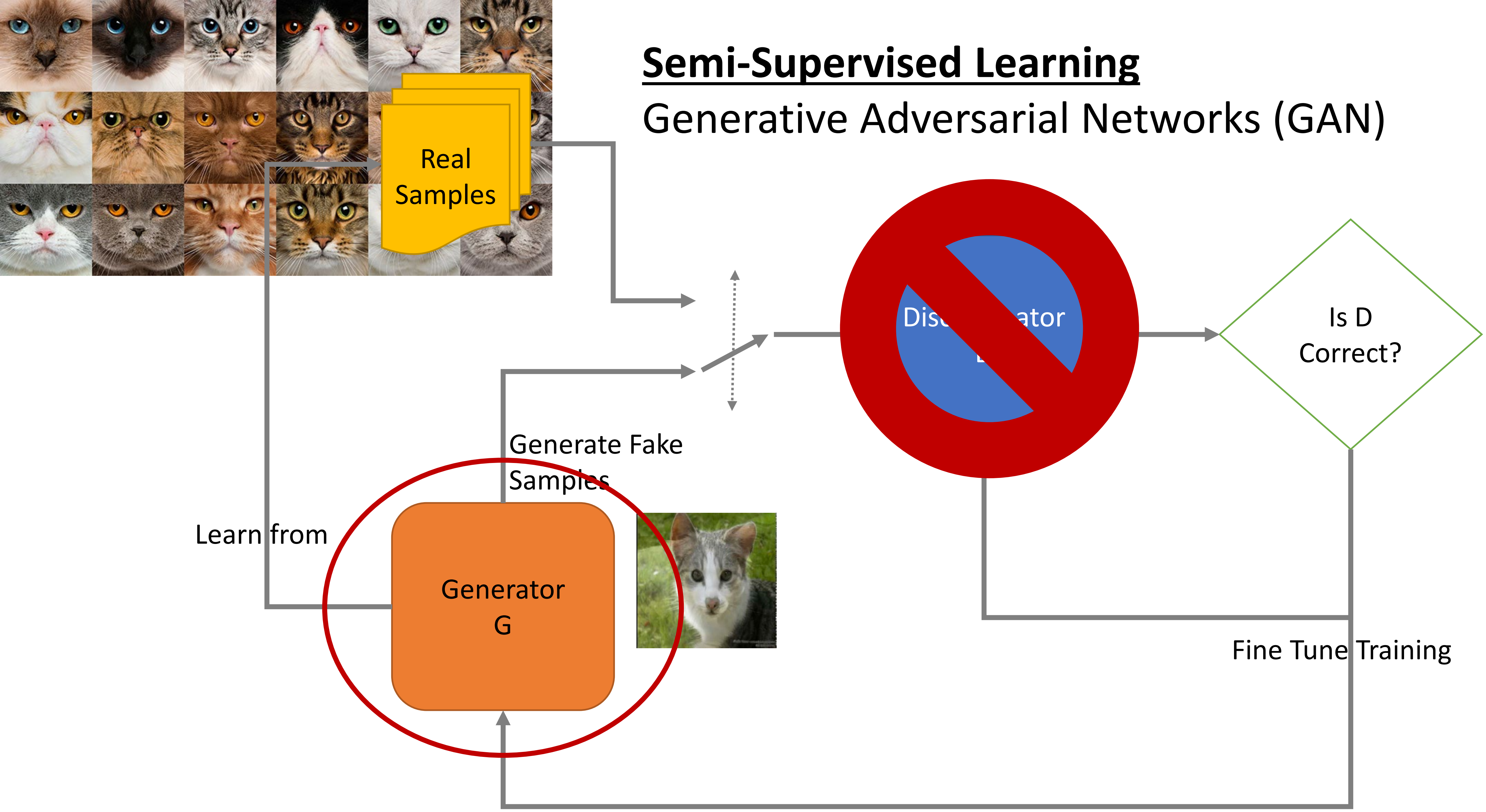
- She committed a $100M fraud in a European bank last year by guessing the admin password using AI algorithm
- She is actually a man dressed in disguise to fool the airport security smuggling 500 fake passports (with valid passport numbers produced by AI) in US last year
- The person inventing this 3rd approach AI algorithm

For more information about stylegan, click the links below

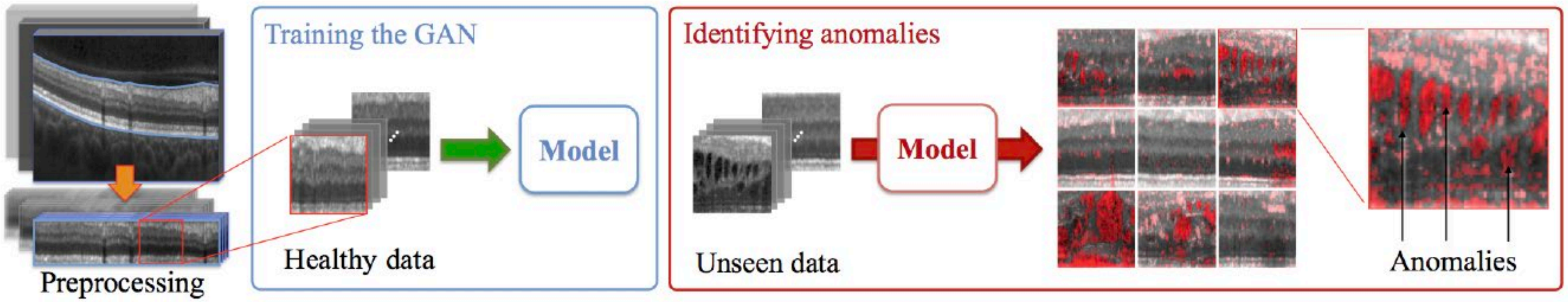
http://stylegan.xyz /paper
https://github.com/NVlabs/stylegan

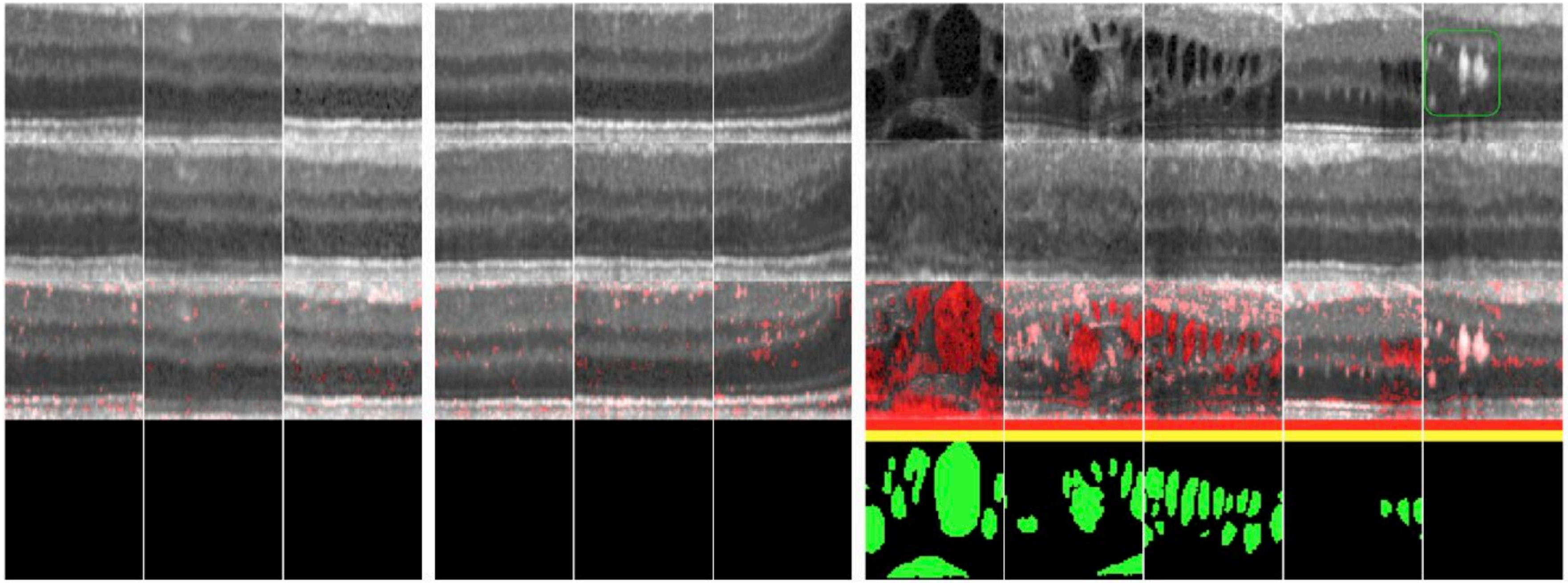
Semi-Supervised Learning

Generative Adversarial Networks (GAN)



AnoGAN

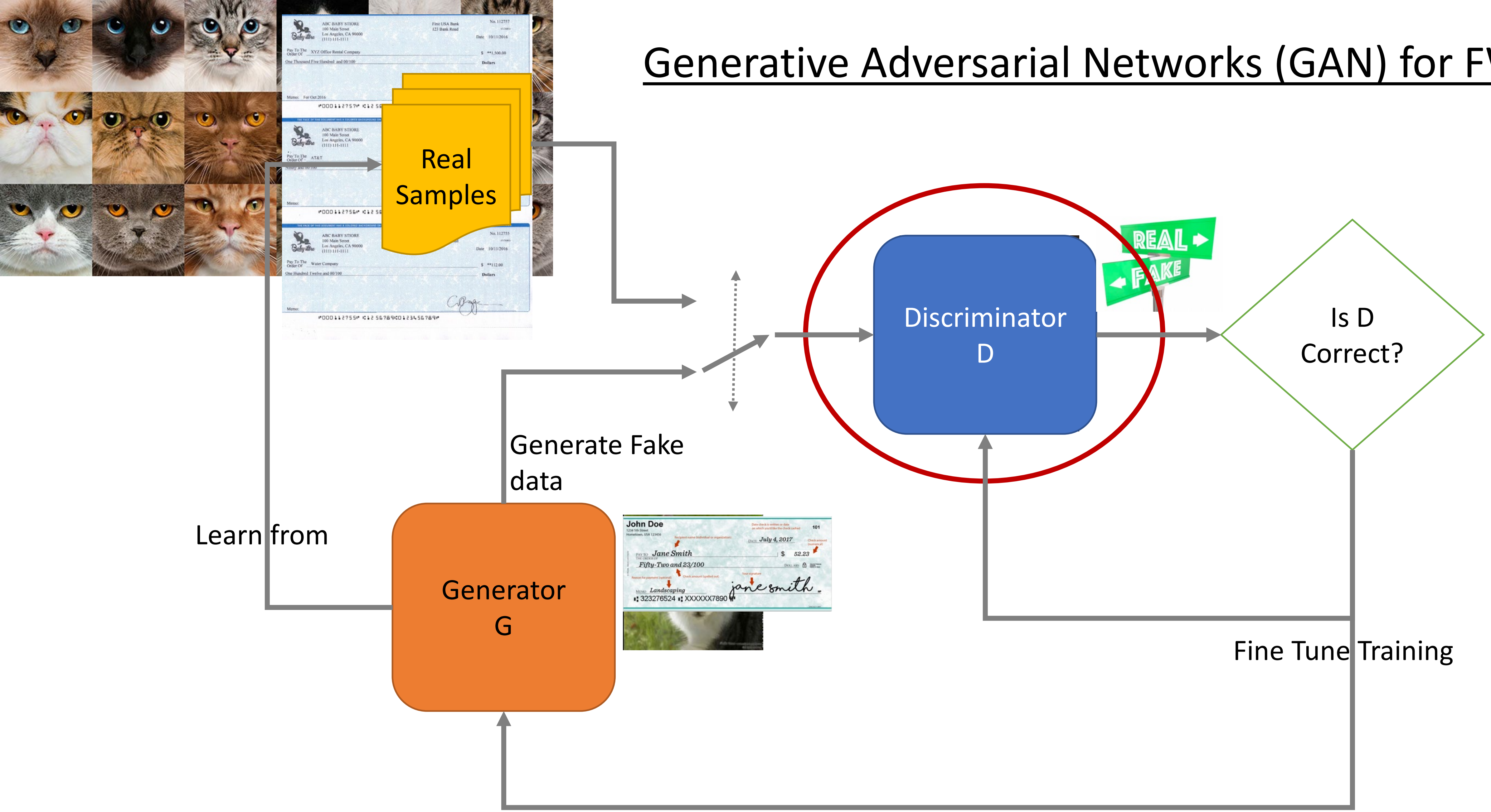




Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery: Thomas Schlegl, Philipp Seeb□ock, Sebastian M. Waldstein, Ursula Schmidt-Erfurth, and Georg Langs (Medical University Vienna, Austria)
http://arxiv.org/abs/1703.05921

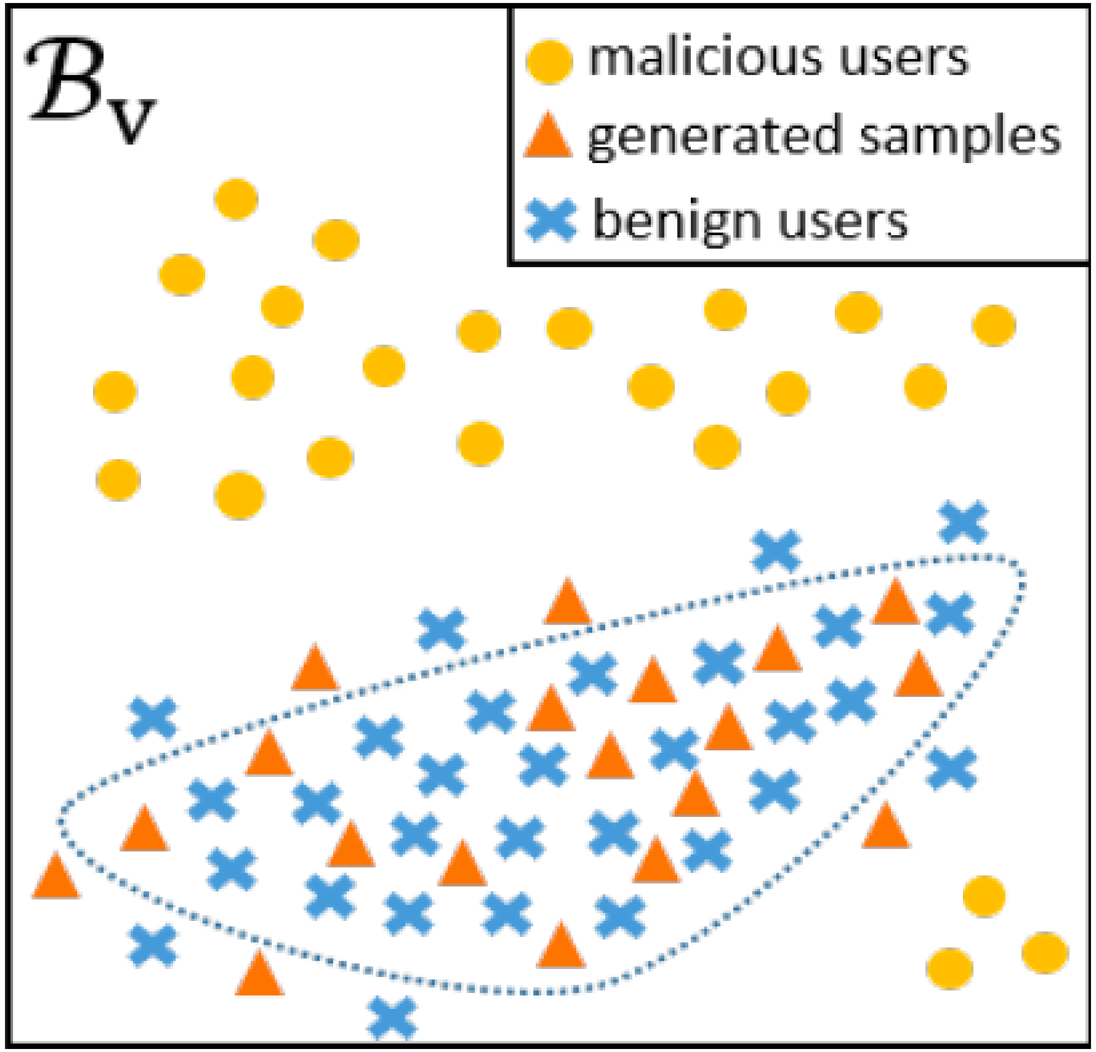
But we are talking about FWA, right?!

Generative Adversarial Networks (GAN) for FWA



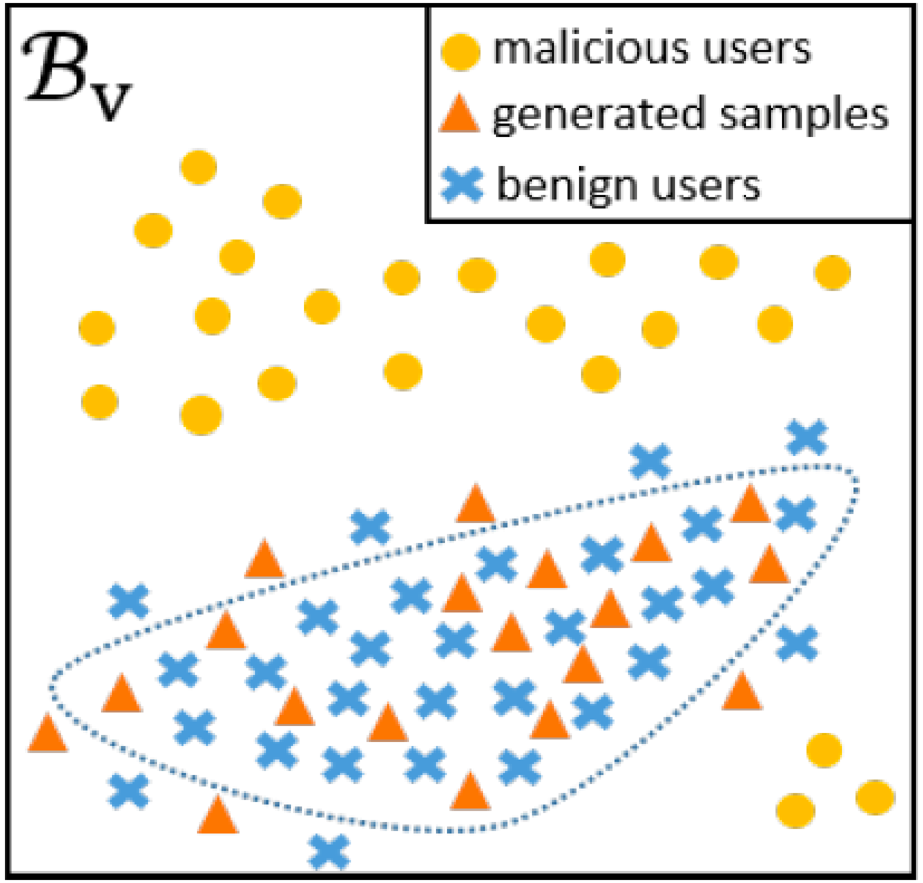
https://www.youtube.com/watch?v=pJBS5SEmlMc
https://www.27machines.com/machine-learning-basics/

Traditional GAN

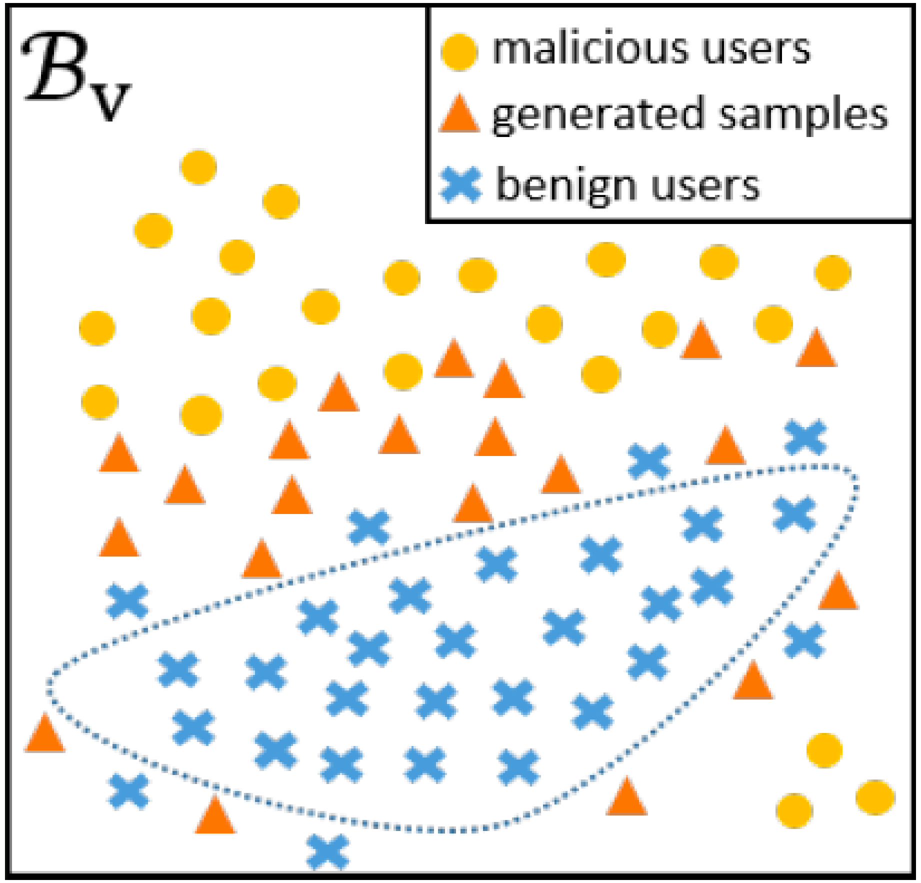


See “One-Class Adversarial Nets for Fraud Detection.” Click the link below. https://arxiv.org/pdf/1803.01798.pdf

One-Class Adversarial Nets (OCAN) GAN



(a) Regular GAN



(b) Complementary GAN

See "One-Class Adversarial Nets for Fraud Detection." Click the link below.
https://arxiv.org/pdf/1803.01798.pdf

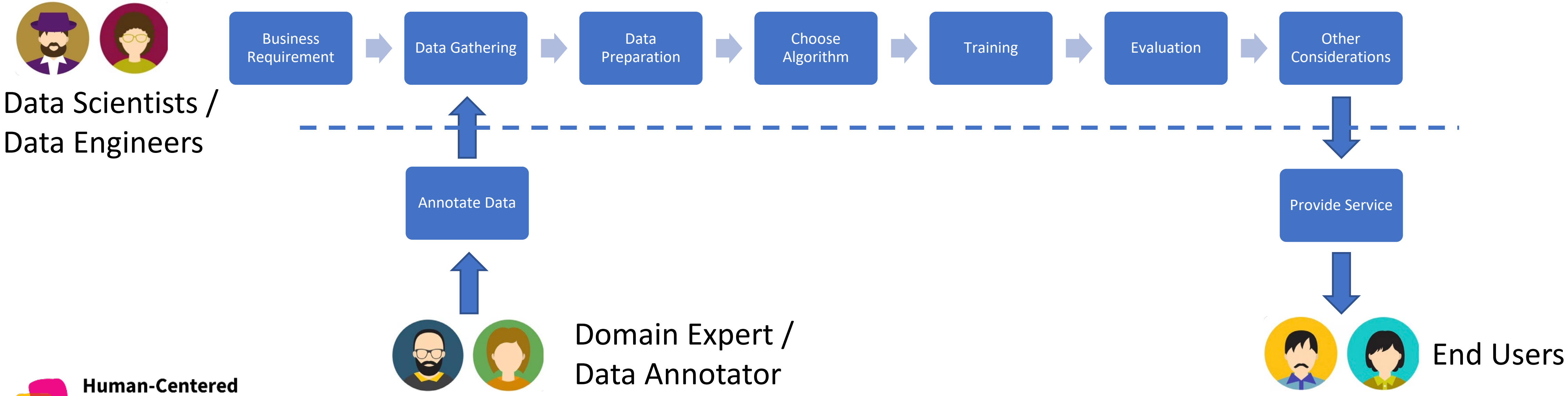
Advantage of One-Class Adversarial Nets

- No need for fraud data
  - No need to manually prepare a mixed training data set, which is usually has a very few fraud data to start with
- Discriminator will take in either real benign or generated malicious
  - More adaptive to different kinds of malicious behavior
- Adapt to newly emerged normal user pattern

Recap: What we have talked about so far…

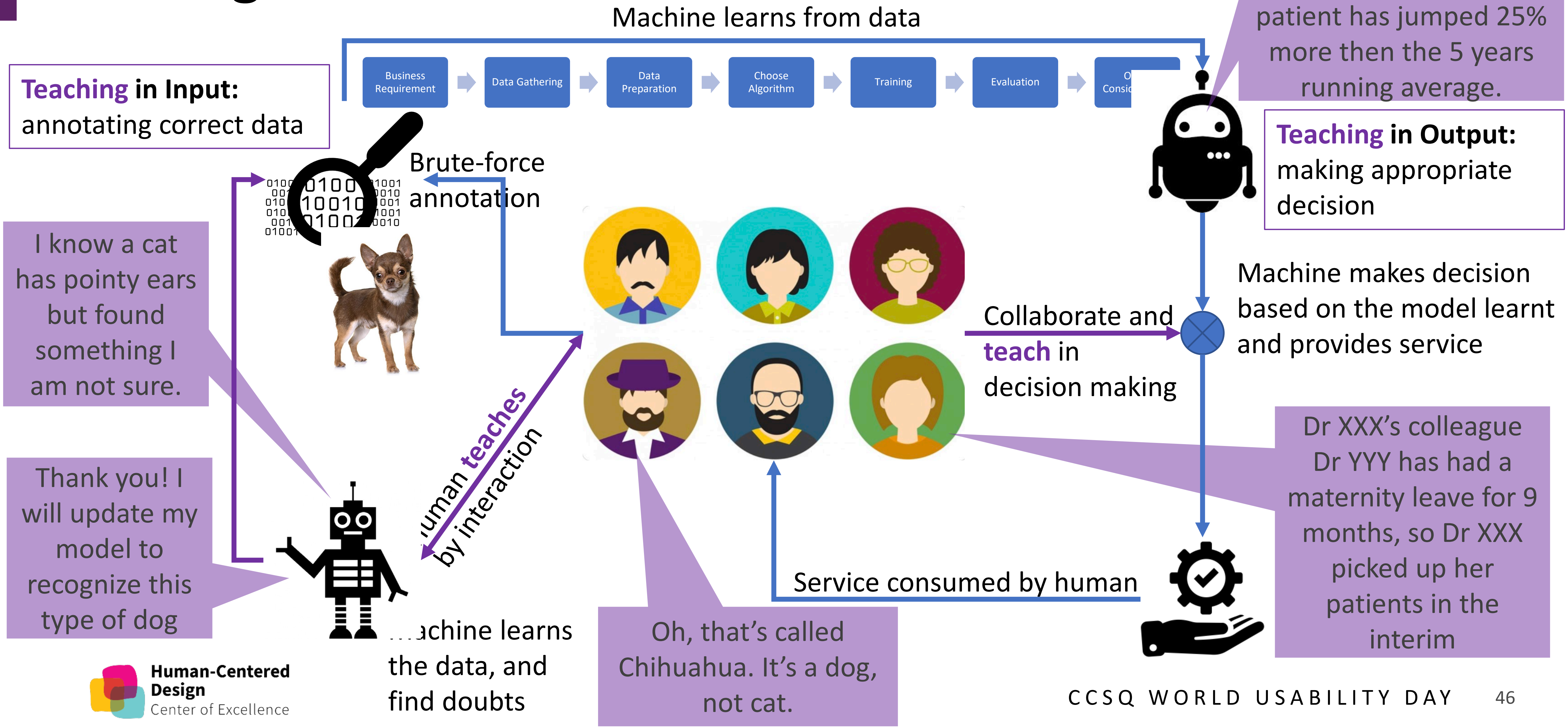
AI Recipe for Data Kitchen (for Machine Learning)

https://www.linkedin.com/pulse/airon-chef-cook-up-ai-your-data-kitchen-cupid-chan/
https://www.youtube.com/watch?v=xifaCq4F7bg

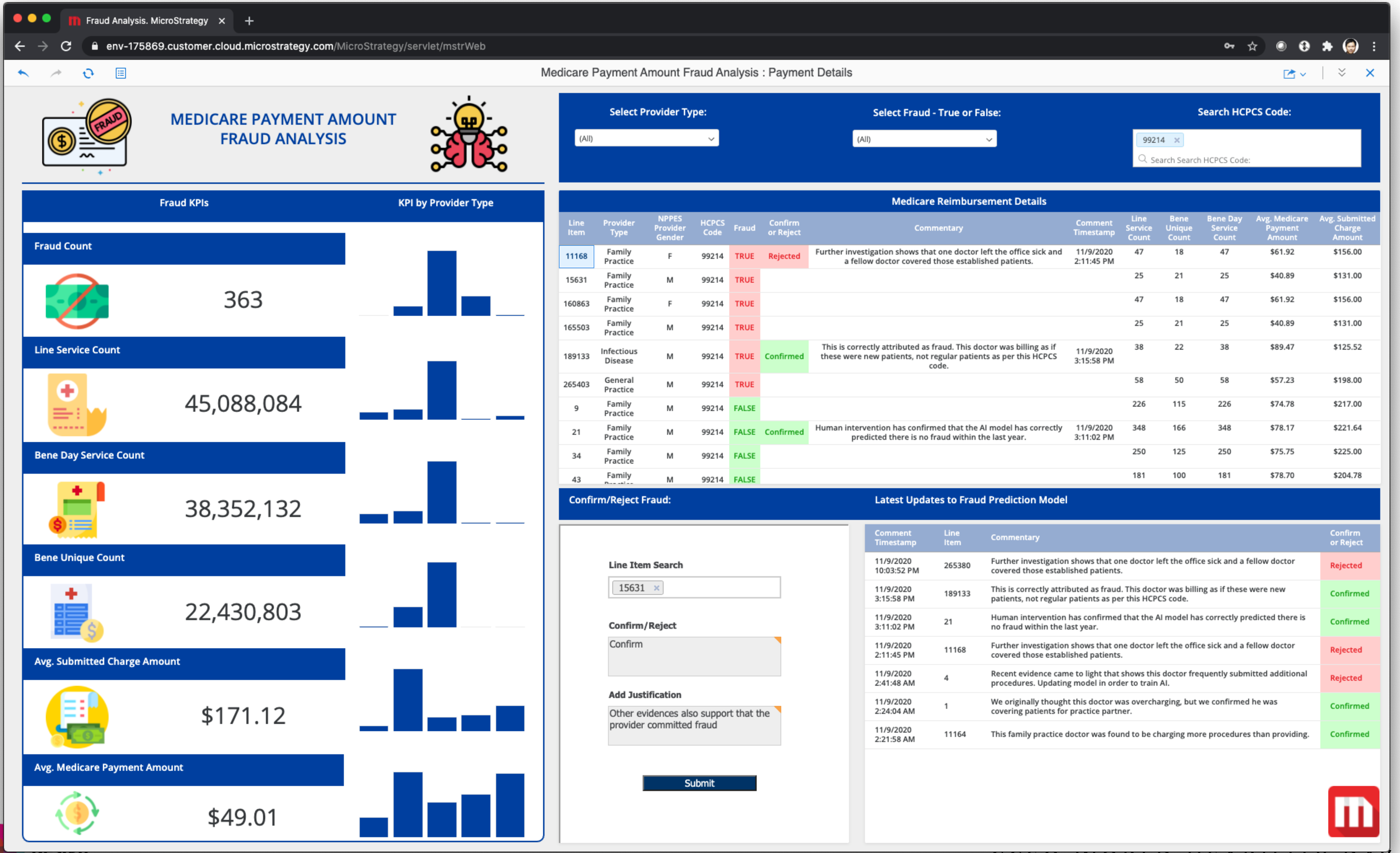


Human-Centered Design Center of Excellence

Human-Centered AI – Machine Learning and Teaching



Human-Centered Design Center of Excellence



Medicare Reimbursement Details

Line Item	Provider Type	NPPES Provider Gender	HCPCS Code	Fraud	Confirm or Reject	Commentary	Comment Timestamp	Line Service Count	Bene Unique Count	Bene Day Service Count	Avg. Medicare Payment Amount	Avg. Submitted Charge Amount
11168	Family Practice	F	99214	TRUE	Rejected	Further investigation shows that one doctor left the office sick and a fellow doctor covered those established patients.	11/9/2020 2:11:45 PM	47	18	47	$61.92	$156.00
15631	Family Practice	M	99214	TRUE				25	21	25	$40.89	$131.00
160863	Family Practice	F	99214	TRUE				47	18	47	$61.92	$156.00
165503	Family Practice	M	99214	TRUE				25	21	25	$40.89	$131.00
189133	Infectious Disease	M	99214	TRUE	Confirmed	This is correctly attributed as fraud. This doctor was billing as if these were new patients, not regular patients as per this HCPCS code.	11/9/2020 3:15:58 PM	38	22	38	$89.47	$125.52
265403	General Practice	M	99214	TRUE				58	50	58	$57.23	$198.00
9	Family Practice	M	99214	FALSE				226	115	226	$74.78	$217.00
21	Family Practice	M	99214	FALSE	Confirmed	Human intervention has confirmed that the AI model has correctly predicted there is no fraud within the last year.	11/9/2020 3:11:02 PM	348	166	348	$78.17	$221.64
34	Family Practice	M	99214	FALSE				250	125	250	$75.75	$225.00
43	Family	M	99214	FALSE				181	100	181	$78.70	$204.78

Latest Updates to Fraud Prediction Model

Comment Timestamp	Line Item	Commentary	Confirm or Reject
11/9/2020 10:03:52 PM	265380	Further investigation shows that one doctor left the office sick and a fellow doctor covered those established patients.	Rejected
11/9/2020 3:15:58 PM	189133	This is correctly attributed as fraud. This doctor was billing as if these were new patients, not regular patients as per this HCPCS code.	Confirmed
11/9/2020 3:11:02 PM	21	Human intervention has confirmed that the AI model has correctly predicted there is no fraud within the last year.	Confirmed
11/9/2020 2:11:45 PM	11168	Further investigation shows that one doctor left the office sick and a fellow doctor covered those established patients.	Rejected
11/9/2020 2:41:48 AM	4	Recent evidence came to light that shows this doctor frequently submitted additional procedures. Updating model in order to train AI.	Rejected
11/9/2020 2:24:04 AM	1	We originally thought this doctor was overcharging, but we confirmed he was covering patients for practice partner.	Confirmed
11/9/2020 2:21:58 AM	11164	This family practice doctor was found to be charging more procedures than providing.	Confirmed

When you talk about AI, think of IA!

Artificial Intelligence

VS

Intelligence Augmentation

AI + BI = CI

AI (Artificial Intelligence) – Excellence in learning with speed

BI (Business Intelligence) – Historically proven to enable human intuited the direction

CI – (Cognitive Intelligence) - Intelligence by combining the Speed of how a Machine Learn and Direction Intuited from Human Insight

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Center of Excellence

2017 CONFERENCE ON HEALTH IT AND ANALYTICS (CHITA)

CHITA
CONFERENCE ON HEALTH IT AND ANALYTICS
November 3rd – 4th 2017 | Washington, DC
Presented by the Center for Health Information & Decision Systems

The Conference on Health IT and Analytics (previously known as the Workshop on Health IT & Economics) is an annual health IT and analytics research summit, including a doctoral consortium that each year gathers prominent scholars from more than 40 research institutes, and leading policy and practitioner attendees in a vibrant setting to discuss opportunities and challenges in the design, implementation and management of health information technology and analytics. Its goal is to deepen our understanding of strategy, policy and systems fostering health IT and analytics effective use and to stimulate new ideas with both policy and business implications.

This forum provides a productive venue to facilitate interaction and collaboration among academia, government, and industry. Now in its 8th year, each year CHITA draws over 100 participants.

Hosted by the Center for Health Information & Decision Systems (CHIDS), support for CHITA is provided by the Robert H. Smith School of Business and the University of Michigan School of Public Health.

We hope that you will join us for this engaging, stimulating and fun event!

FEATURED SPEAKERS

Martin "Marty" Makary
Chief, Islet Transplant Surgery, Professor, NYT best-selling author
Johns Hopkins University School of Medicine

Warren D. D'Souza
Vice President, Enterprise Data and Analytics
University of Maryland Medical System

FEATURED PANELISTS

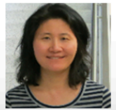
Cupid Chan
Chief Technology Officer
Index Analytics

Rema Padman
Professor of Management Science and Healthcare Informatics
Carnegie Mellon University

Anna T. Fernandez
Senior Associate, Health Informatics
Booz Allen Hamilton

Charles Gabrial
Analytics & Data Science Manager
Defense Health Agency

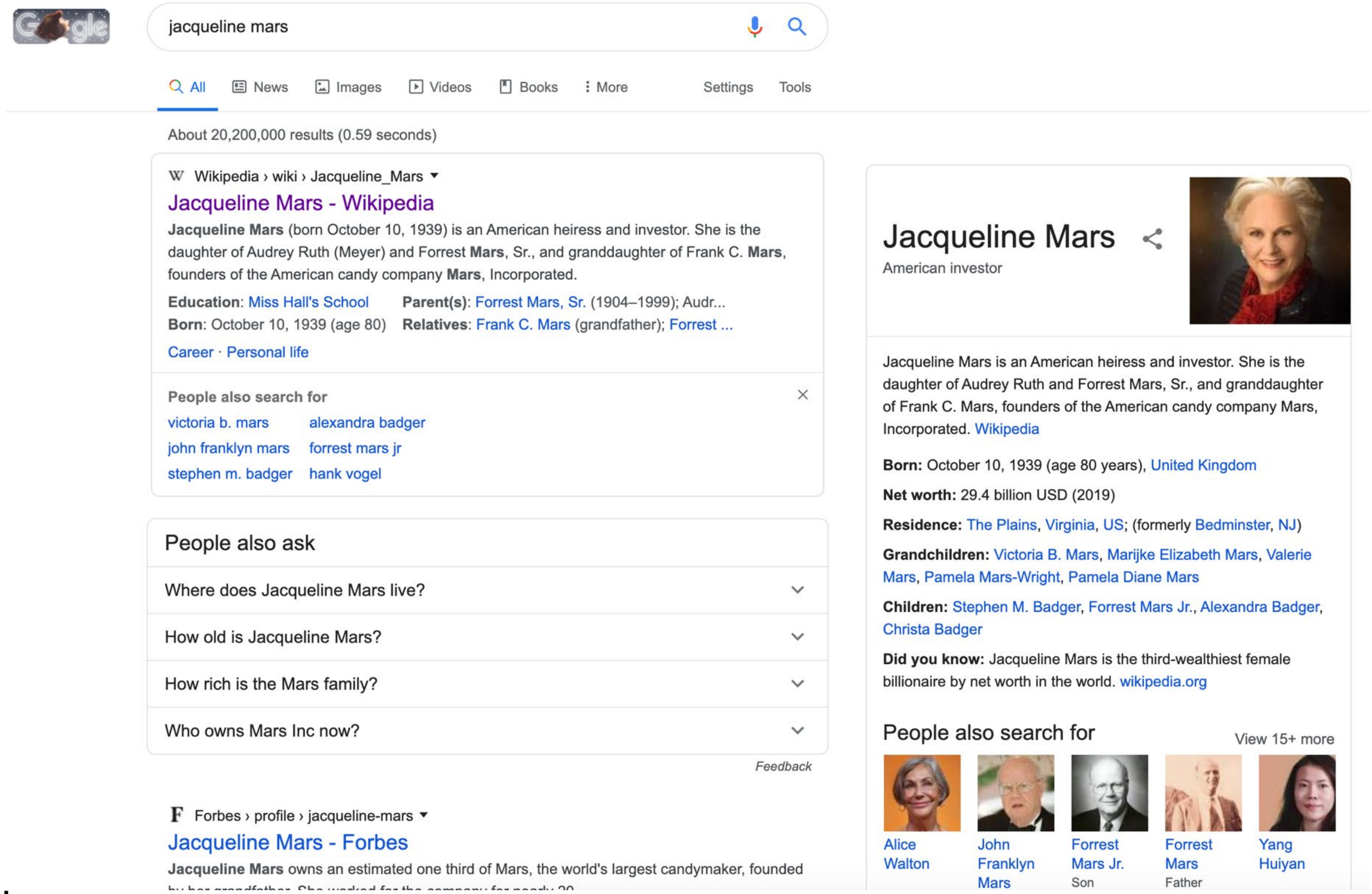
Hoo Chang Shin
Solutions Architect
NVIDIA



Hong Yu
Professor of Quantitative Health Sciences

... LinkedIn Story continues

I decided to find my most knowledgeable friend for help



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Cupid Chan • 10:29 PM

I am sorry, but exactly what?

Jacqueline Mars • 10:31 PM

What you do in your place of work and the profitable it is.

Cupid Chan • 10:31 PM

i see

Cupid Chan is typing...

Jacqueline Mars • 10:38 PM

Don’t you want to talk to me about it’s fine I’m sorry 😐

Cupid Chan • 10:38 PM

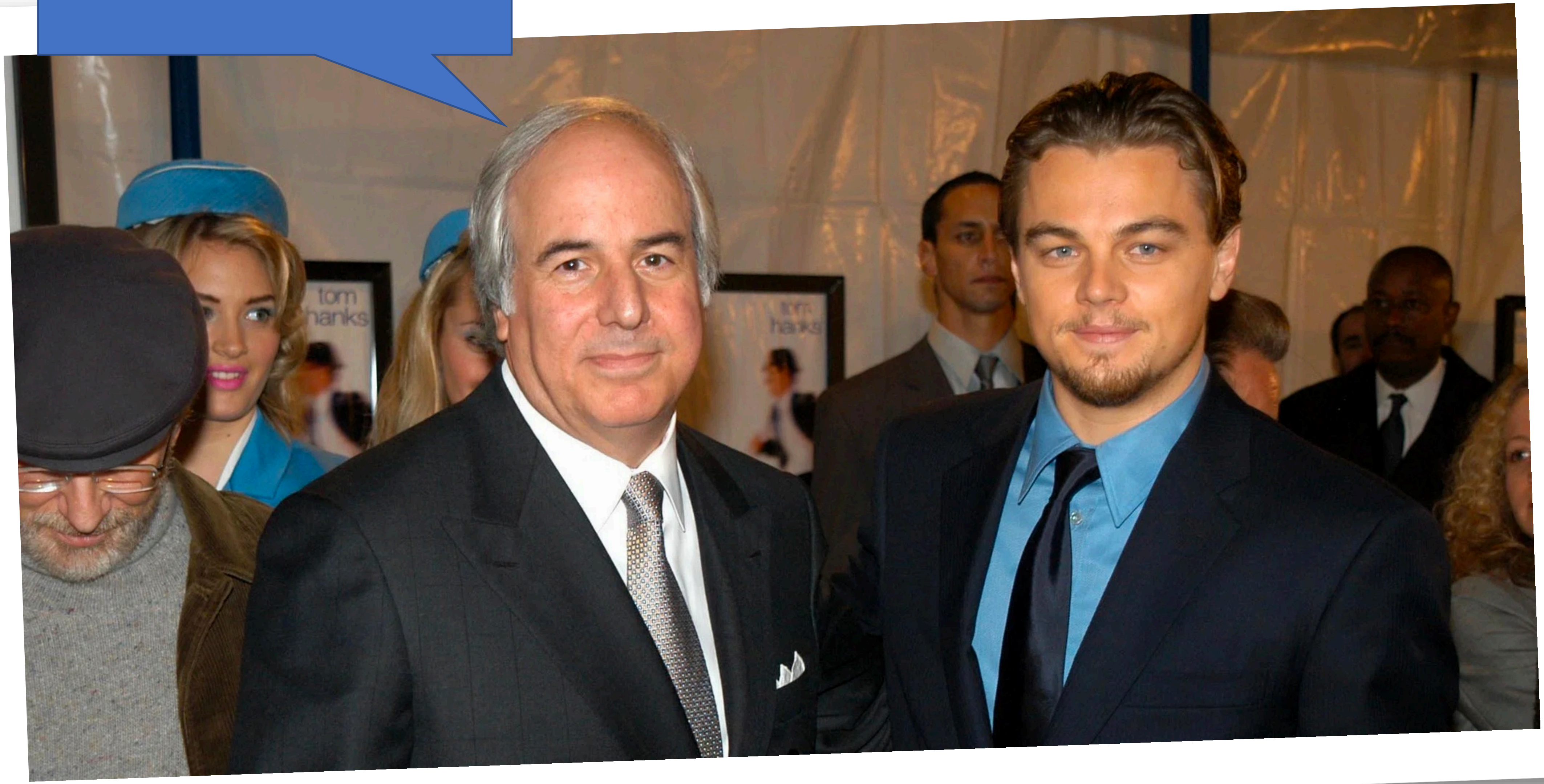
Cupid Chan is a seasoned professional who is well-established in the industry. His journey started out as one of the key players in building a world-class BI platform. Aside from holding various technical accreditations, his credential extends into business

Jacqueline Mars • 10:42 PM

WOW

Cool

The real: Frank Abagnale



Cupid Chan

- Board of Directors and Technical Steering Committee, Chairperson of BI & AI Project, Linux Foundation ODPi
- Senior Fellow & Adjunct Professor, University of Maryland College Park

www.linkedin.com/in/cupidchan/

@cupidckchan