



worldusabilityday

Catch me if you can


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

Cupid Chan
2020-11-12





CCSQ WORLD USABILITY DAY 1

1



+ **DLFAI**



The DLFAI & DATA landscape explores open source projects in artificial intelligence and data and their respective domains.

2

The image shows a LinkedIn profile for Jacqueline Mars on the left and a chat window on the right. The profile includes a profile picture, name, title 'Anthropology at Miss Hall's School', location 'Washington D.C. Metro Area', and '88 connections'. A red box highlights the 'Highlights' section showing '16 mutual connections'. The 'Experience' section lists 'Co-Founder' at 'AMERICAN CANDY CO LIMITED' from Sep 1982 to Sep 2001. The 'Education' section lists 'Miss Hall's School' for 'Anthropology'. The chat window shows a conversation between Jacqueline Mars and Cupid Chan. Jacqueline Mars sends a 'Hello' and a longer message about being an investor and hoping to work together. Cupid Chan responds with a welcome message. Jacqueline Mars replies 'Absolutely' and provides her website 'www.mars.com'. Cupid Chan responds 'I am in a Virginian too. Nice to meet you!'.

3

The image shows a chat conversation between Jacqueline Mars and Cupid Chan. Jacqueline Mars asks 'What do you do?'. Cupid Chan responds '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 replies 'Interesting'. Cupid Chan asks '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.'. Jacqueline Mars replies 'Yes, exactly'. Cupid Chan asks 'By "exclusive", you mean in what sense?'. Jacqueline Mars replies 'Yes, exactly'. Cupid Chan asks 'I am sorry, but exactly what?'.

4

LinkedIn Story to be continued...



5

10 seconds Polling Question

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



6



7

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

catch me

if you can

Presented by Cupid Chan

8

Fraud, Waste, Abuse and Error



Fraud

Intentional Deception



Abuse

Bending the rules



Waste

Inefficiency



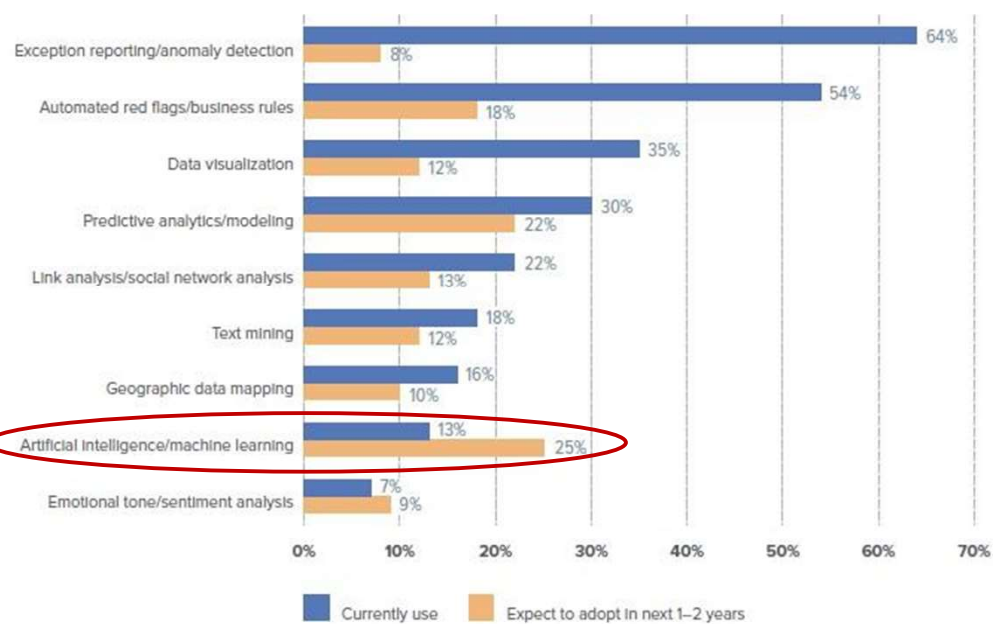
Error

Unintentional fault



9

FIG. 1 What data analysis techniques do organizations use to fight fraud?



<https://www.forbes.com/sites/louiscolombus/2019/08/01/ai-is-predicting-the-future-of-online-fraud-detection/#1a19bfa374f5>

10

10 seconds Polling Question - 1

Which of the following popular fraud costing the most?

- Credit card Fraud
- Healthcare Fraud
- Identity Fraud



11

• Healthcare fraud: \$68 billion per year

• Credit card fraud: \$24.71 billion in 2016

• Identity Fraud: 1.7 billion

<https://www.bcbcm.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-look-for-new-targets-and-victims-bear-brunt>

12

The screenshot shows the HHS.gov website with the following content:

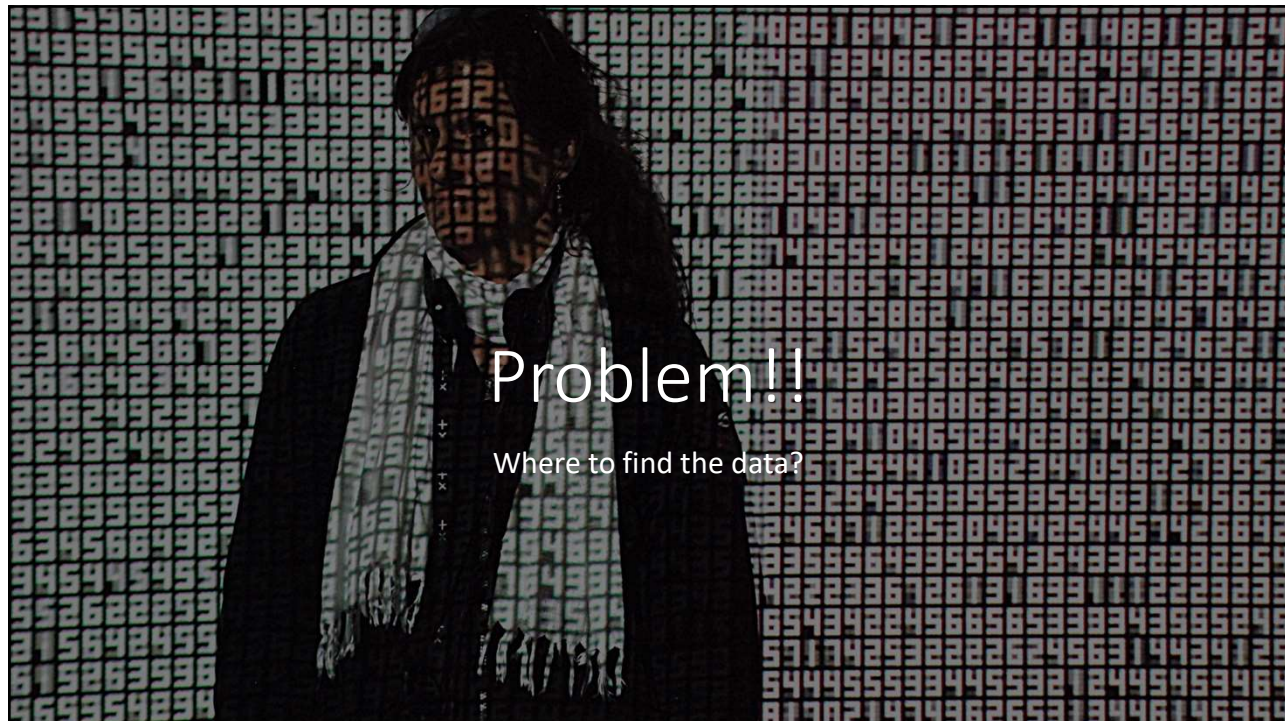
- Navigation:** About HHS, Programs & Services, Grants & Contracts, Laws & Regulations.
- Page Title:** HHS FY 2018 Budget in Brief - CMS - Overview
- Section:** Centers for Medicare & Medicaid Services (CMS): Overview
- Text:** The Centers for Medicare & Medicaid Services ensures availability of effective, up-to-date health care coverage and promotes quality care for beneficiaries.
- Table:** CMS Budget Overview (Dollars in millions)

Category	Amount (Dollars in millions)
Current Law	1.0
Medicare	2
Medicaid	3
CHIP	4
State Grants and Demonstrations	5
Other Health Insurance Programs	6
Center for Medicare and Medicaid Innovation	7
Total Net Outlays, Current Law	8
- ABC News Report:** Medicare Funds Totaling \$60 Billion Improperly Paid, Report Finds. By JIM AVILA, SERENA MARSHALL AND GITIKA KAUL. Jul 23, 2015, 5:59 PM ET.
- Video Player:** A video player showing a news anchor with a graphic that says "YOUR MONEY" and a play button.
- World Population Review Table:**

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	1,433,783,886
3	Japan	5.18 trillion	4.94 trillion	\$40,802	128,860,301
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	2.60 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
9	Spain	1.97 trillion	1.80 trillion	\$9,288	211,049,527
10	Canada	1.53 trillion	\$46,487	37,411,047	
11	South Korea	1.41 trillion	\$32,341	51,225,308	
12	Sweden	1.25 trillion	\$11,040	145,872,256	
13	Netherlands	1.24 trillion	\$30,578	46,736,776	
14	Belgium	1.30 trillion	\$56,223	25,203,198	
15	Australia	1.08 trillion	\$9,731	127,575,529	
16	South Africa	932.26 billion	\$4,068	270,825,568	
17	Israel	777.23 billion	\$53,459	17,097,130	
18	Brazil	639.62 billion	\$22,244	34,268,828	
19	Mexico	668.85 billion	\$82,358	8,591,365	
20	Russia	863.71 billion	\$8,485	83,429,615	
21	U.S. Territories	\$29,296	23,773,876		

> \$1 Trillion

13



14

Medicare Provider Utilization and Payment Data: Physician and Other Supplier

The screenshot shows the CMS.gov website with the following elements:

- Header: CMS.gov, Centers for Medicare & Medicaid Services
- Navigation: Home, About CMS, Newsroom, Archive, Share, Help, Print
- Search: type search term here
- Menu: Medicare, Medicaid/CHIP, Medicare-Medicaid Coordination, Private Insurance, Innovation Center, Regulations & Guidance, Research, Statistics, Data & Systems, Outreach & Education
- Breadcrumbs: Home > Research, Statistics, Data and Systems > Medicare Provider Utilization and Payment Data > Medicare Provider Utilization and Payment Data: Physician and Other Supplier
- Section: Medicare Provider Utilization and Payment Data: Physician and Other Supplier
- Description: 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.
- Additional Info: 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.
- 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

15

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	## nppes_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	## stdev_Medicare_allowed_amt	## stdev_Medicare_allowed_amt	## AVERAGE_MedicARE_ALLOWED_AMT	## average_Medicare_allowed_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
## AVERAGE_MedicARE_PAYMENT_AMT	## AVERAGE_MedicARE_PAYMENT_AMT	## average_Medicare_standard_amt	## average_Medicare_standard_amt	## AVERAGE_MedicARE_STANDARD_AMT	## average_Medicare_standard_amt
## STDEV_SUBMITTED_CHRG_AMT	## STDEV_SUBMITTED_CHRG_AMT				
## STDEV_MedicARE_PAYMENT_AMT	## STDEV_MedicARE_PAYMENT_AMT				
## STDEV_MedicARE_PAYMENT_AMT	## STDEV_MedicARE_PAYMENT_AMT				

16

List of Excluded Individuals and Entities (LEIE)

Exclusions Program

This webpage provides information about OIG's exclusion authority and activities. OIG has the authority to exclude individuals and entities from Federally funded health care programs for a variety of reasons, including a conviction for Medicare or Medicaid fraud. Those that are excluded can receive no payment from Federal healthcare programs for any items or services they furnish, order, or prescribe. This includes those that provide health benefits funded directly or indirectly by the United States (other than the Federal Employees Health Benefits Plan).

- Online Searchable Database
- LEIE Downloadable Databases
- Monthly Supplement Archive
- Quick Tips
- Waivers
- Background Information
- Applying for Reinstatement

LEIE Downloadable Databases

10-08-2020
Last Update

LEIE Database

- 09-2020 Updated LEIE Database (CSV)

Current Monthly Supplements

- 09-2020 Exclusions (CSV)
- 09-2020 Reinstatements (CSV)
- Monthly Supplement Archive

Profile Updates

- 09-2020 Profile Corrections

Current Record Layout

- Current Database Record Layout

17

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

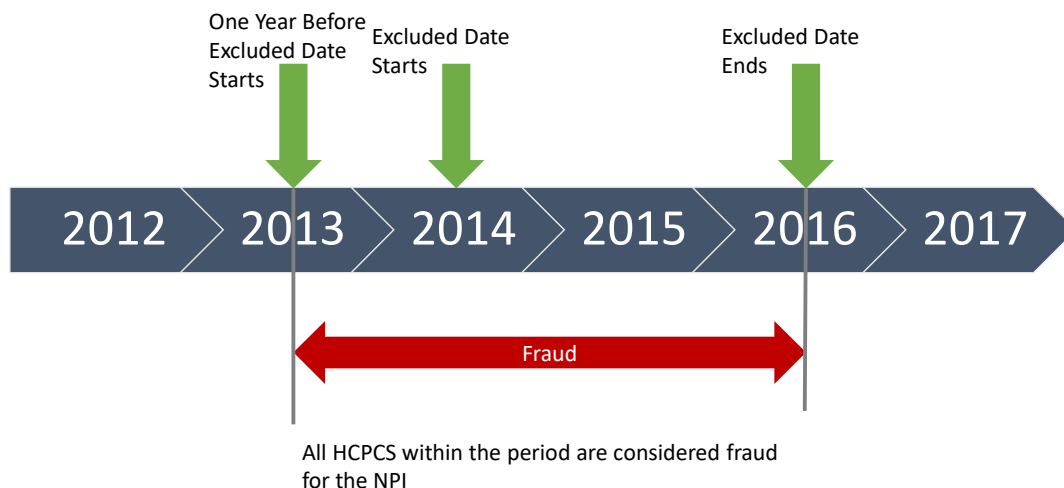
Mandatory Exclusions

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

<https://oig.hhs.gov/exclusions/authorities.asp>

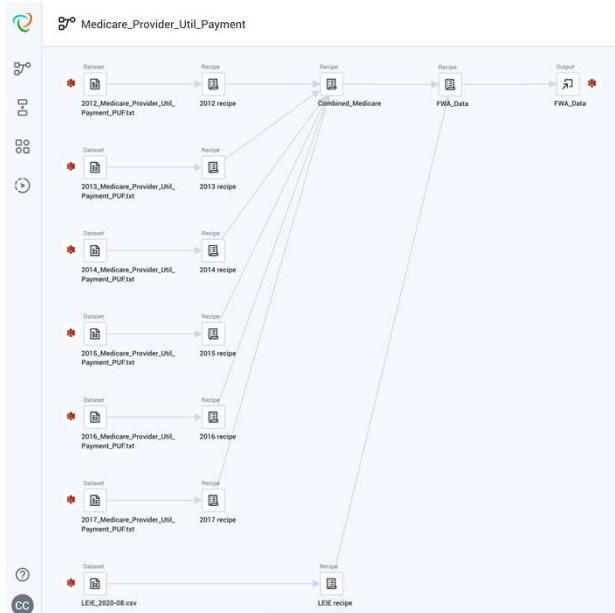
18

Define what is fraud based on the data set



19

Overall data ingestion flow



20

Final data set structure

RBC	provider_type	Provider's specialty, e.g. Internal Medicine, Dermatology
👤	nppes_provider_gender	Provider Gender
RBC	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



21

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 NOT Fraud



22

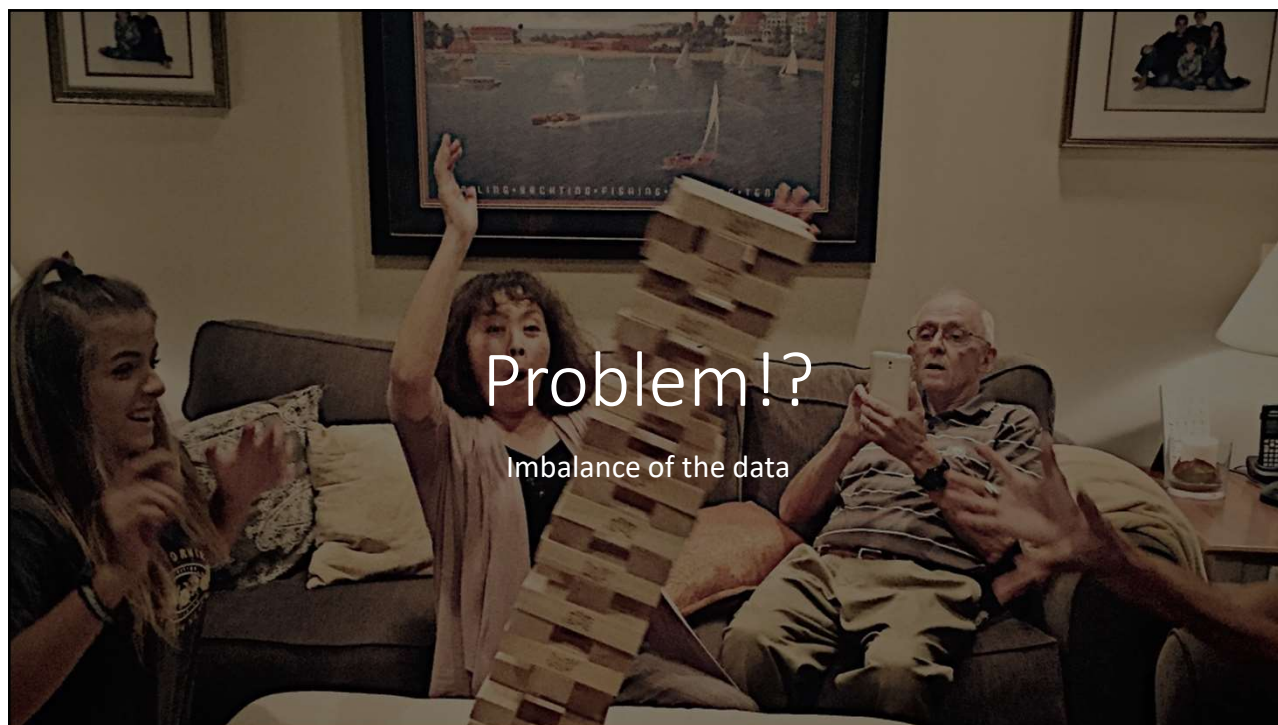
Confusion Matrix

- 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 $\frac{TP + TN}{TP + TN + FP + FN}$



23



24



The slide features a dark grey background. On the left, three chocolate cookies with happy faces are grouped together. On the right, a single chocolate cookie with a sad face stands alone. The text and list are centered between these two groups.

Data Discrimination – Minority Class

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

25



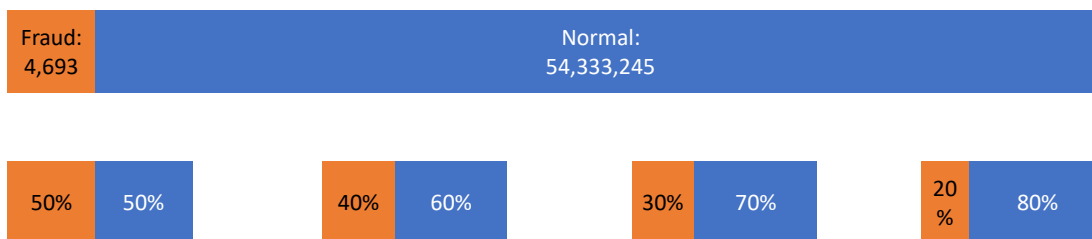
The slide features a white background with a 3D graphic of a blue ribbon and an orange arrow pointing upwards, set against a backdrop of business charts and documents. The text and list are positioned on the left side of the slide.

Potential Solution for Class Imbalance

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

26

Random Under Sampling (RUS)



27

```
1 import tensorflow as tf
2 CATEGORICAL_COLUMNS = ['appes_provider_gender', 'provider_type', 'hpcs_code']
3 INT_COLUMNS = ['time_serve_cnt', 'home_unique_cnt', 'home_dsp_serve_cnt']
4 FLOAT_COLUMNS = ['average_submitted_chrg_amt', 'average_medicare_payment_amt']
5
6
7 feature_columns = []
8 for feature_name in CATEGORICAL_COLUMNS:
9     vocabulary = tf.train.FeatureNameVocabulary()
10    feature_columns.append(tf.feature_column.categorical_column_with_vocabulary_list(feature_name, vocabulary))
11
12 for feature_name in FLOAT_COLUMNS:
13    feature_columns.append(tf.feature_column.numeric_column(feature_name, dtype=tf.float32))
14
15 for feature_name in INT_COLUMNS:
16    feature_columns.append(tf.feature_column.numeric_column(feature_name, dtype=tf.int16))
17
18 # Use entire batch since this is such a small dataset.
19 NUM_EXAMPLES = len(y_train)
20
21 def make_input_fn(X, y, n_epochs=None, shuffle=True):
22     def input_fn():
23         dataset = tf.data.Dataset.from_tensor_slices((dict(X), y))
24         if shuffle:
25             dataset = dataset.shuffle(NUM_EXAMPLES)
26         # For training, cycle thru dataset as many times as need (n_epochs=None).
27         dataset = dataset.repeat(n_epochs)
28         # In memory training doesn't use batching.
29         dataset = dataset.batch(NUM_EXAMPLES)
30         return dataset
31     return input_fn
32
33 # Training and evaluation input functions.
34 train_input_fn = make_input_fn(dict(train), y_train)
35 eval_input_fn = make_input_fn(dict(eval), y_eval, shuffle=False, n_epochs=1)
36
37 n_batches = 1
38 est = tf.estimator.BoostedTreesClassifier(feature_columns,
39                                         n_batches_per_layer=n_batches)
40
41 # The model will stop training once the specified number of trees is built, not
42 # based on the number of steps.
43 est.train(train_input_fn, max_steps=100)
44
45 # Eval.
46 result = est.evaluate(eval_input_fn)
47 clear_output()
48 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

28

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



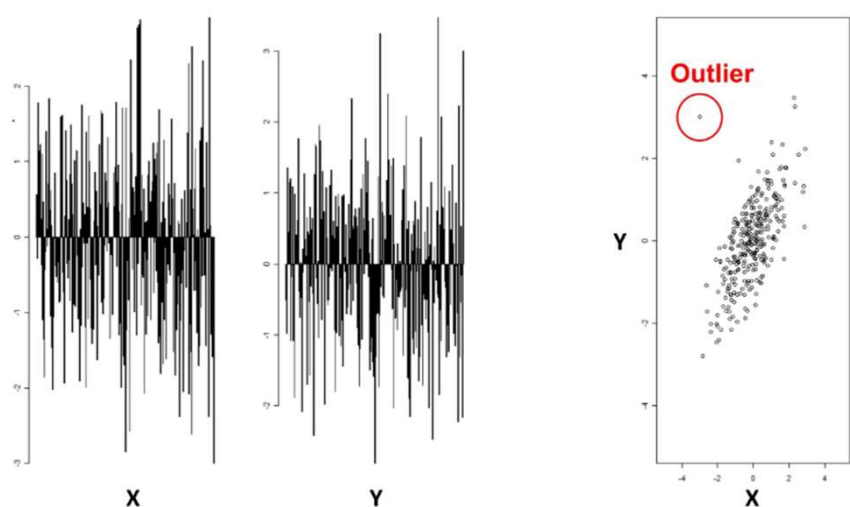
Unsupervised Learning

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



31

Where is the Outlier?

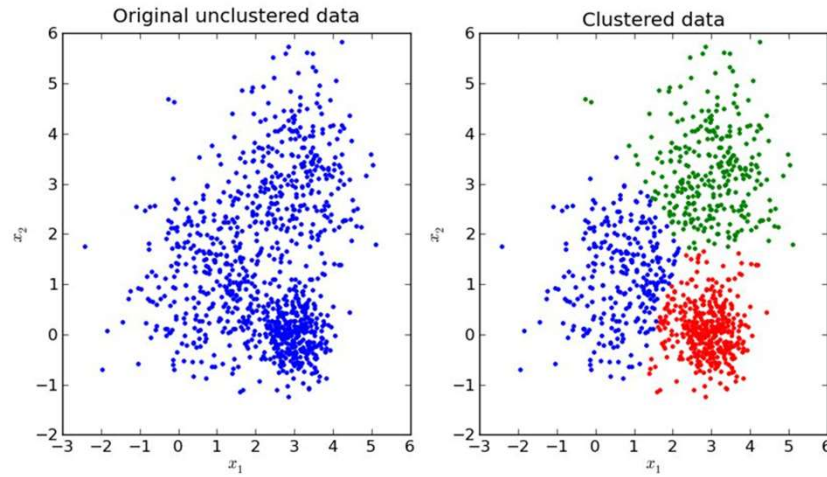


Human-Centered Design
Center of Excellence

CCSQ WORLD USABILITY DAY 32
https://miro.medium.com/max/1944/1*Ba0iTGWAoFi-3-E-rjGdg.jpeg

32

Unsupervised Clustering



CCSQ WORLD USABILITY DAY 33

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

33



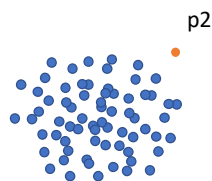
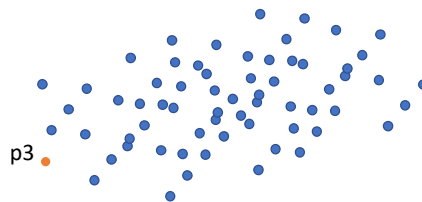
<https://www.youtube.com/watch?v=BmcaUjmo48I&t=4s>

34

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

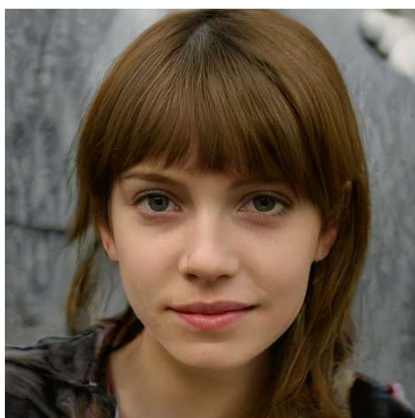
- By density
- Having the lowest density among closest points
- Both p1 and p2 are considered outlier



35

10 seconds Polling Question -3

You must know her for this 3rd approach

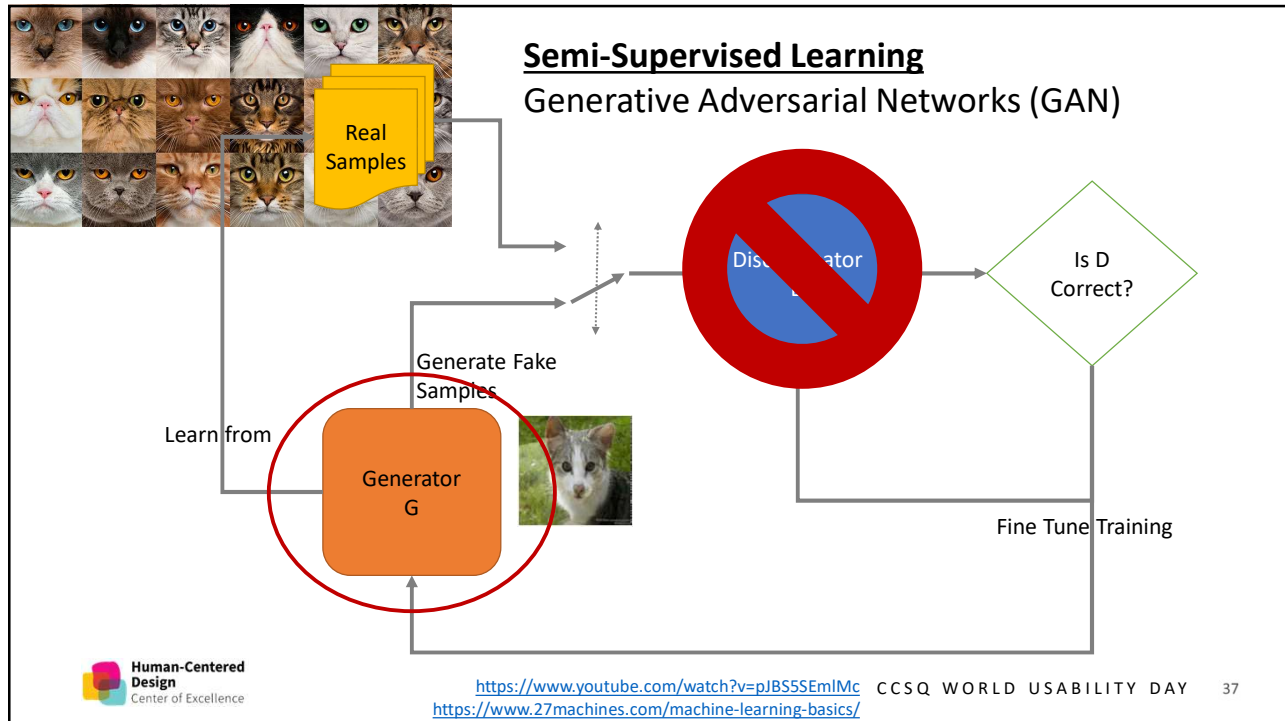


Who is she?

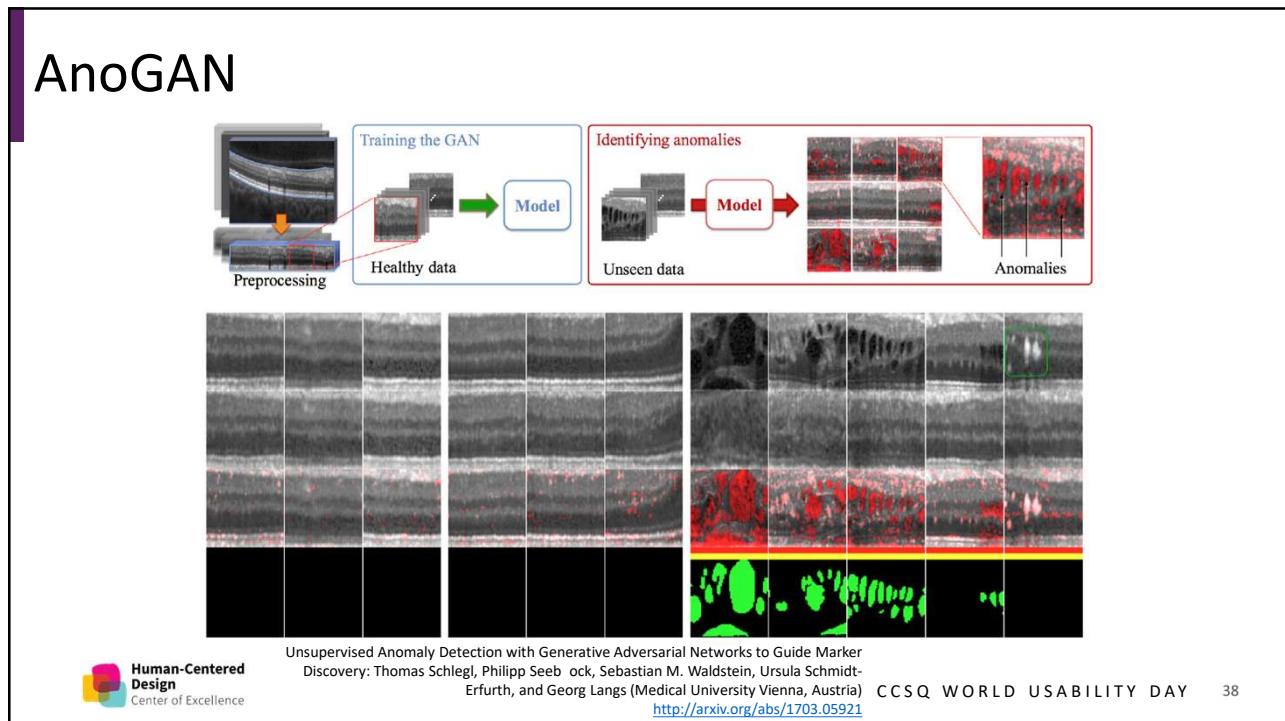
- She committed a \$100M fraud in a European bank last year by guessing the admin password using AI algorithm
- She is an actually a man dressed in disguise to fool the airport security smuggling 500 fake passports (with valid passport numbers produced by AI) in US last year
- The person inventing this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

<http://stylegan.xyz/paper>
<https://github.com/NVLabs/stylegan>

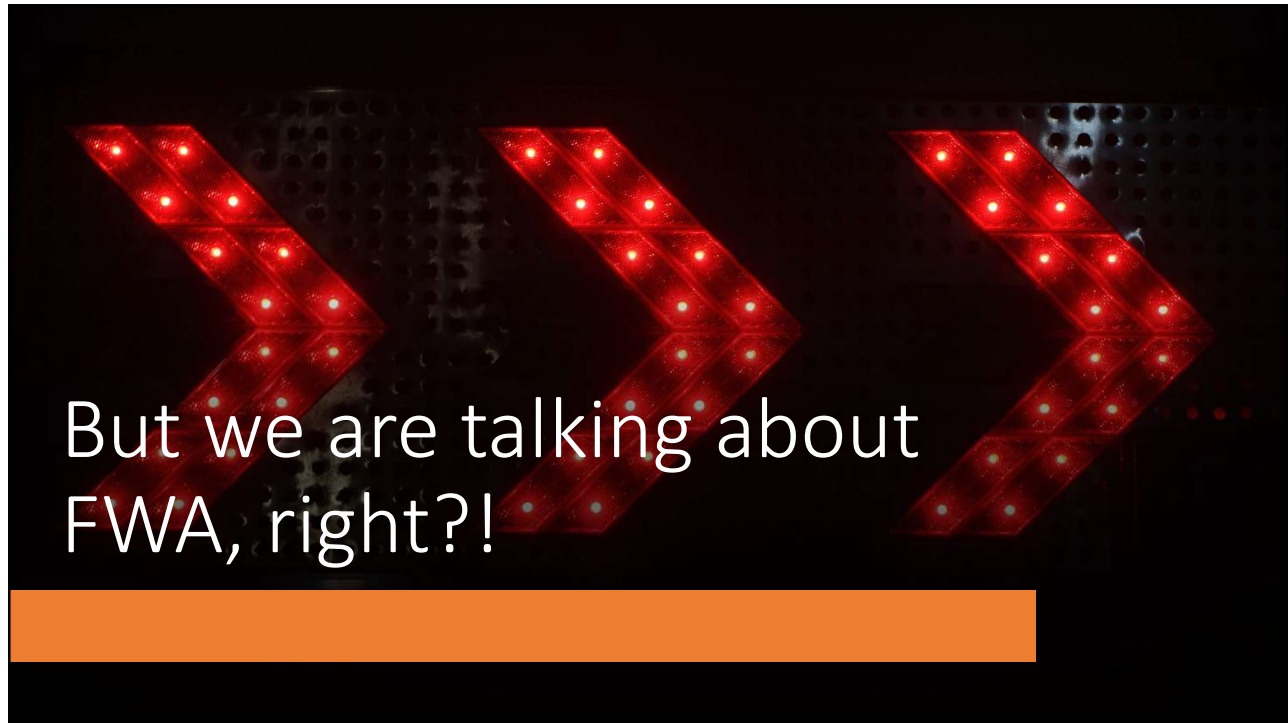
36



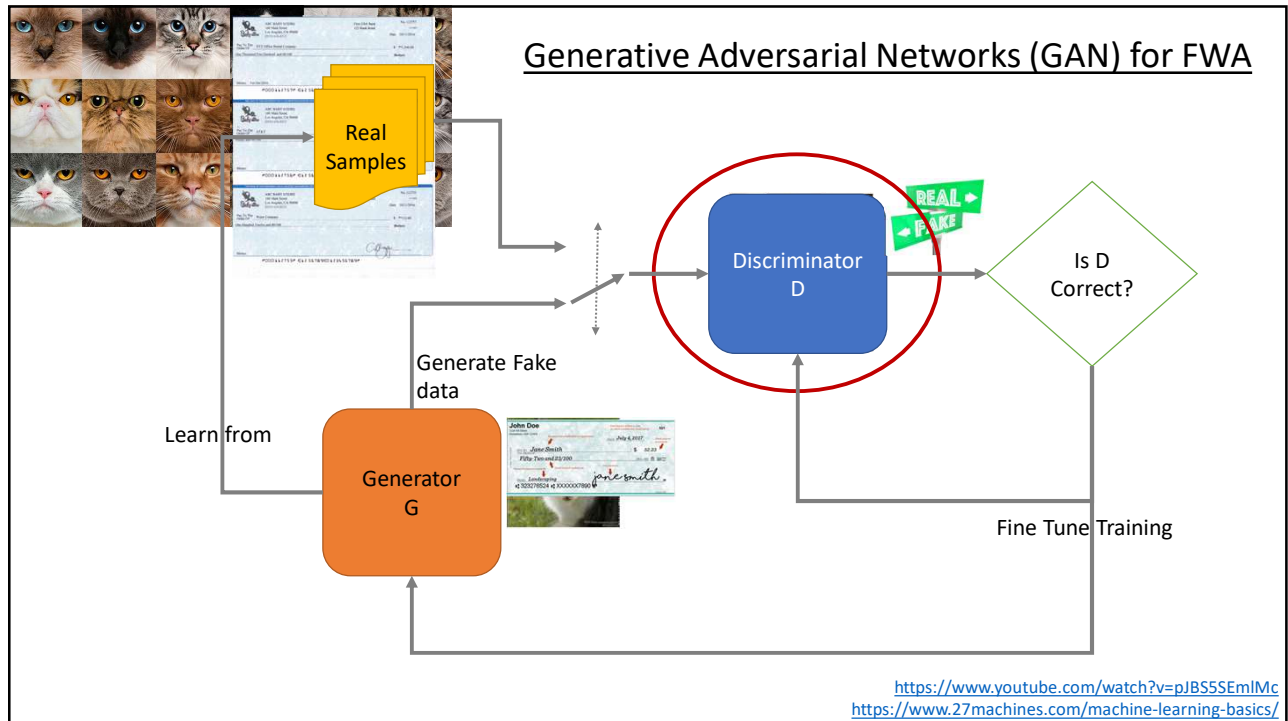
37



38

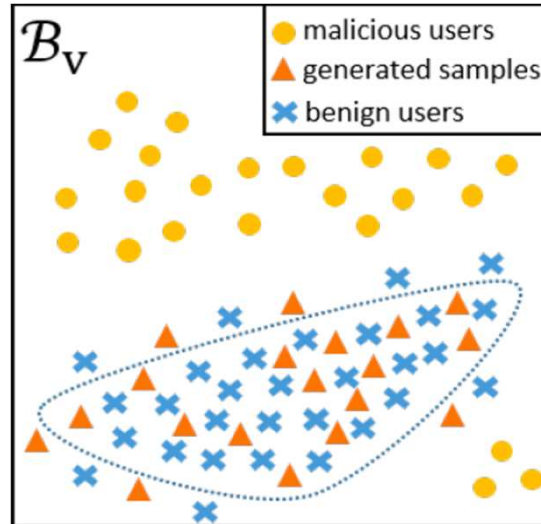


39



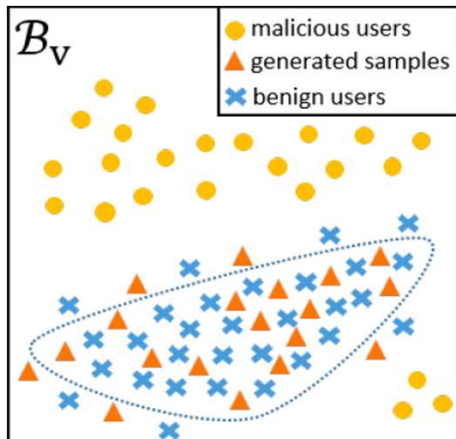
40

Traditional GAN

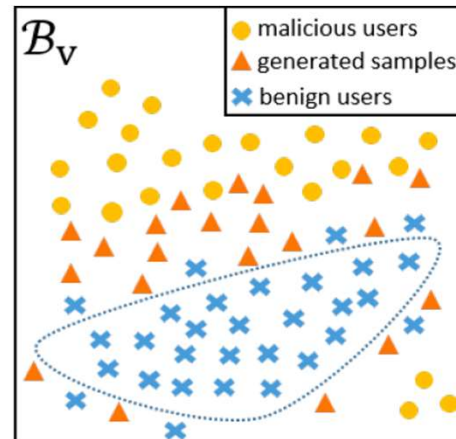


41

One-Class Adversarial Nets (OCAN) GAN



(a) Regular GAN



(b) Complementary GAN

42

Advantage of One-Class Adversarial Nets

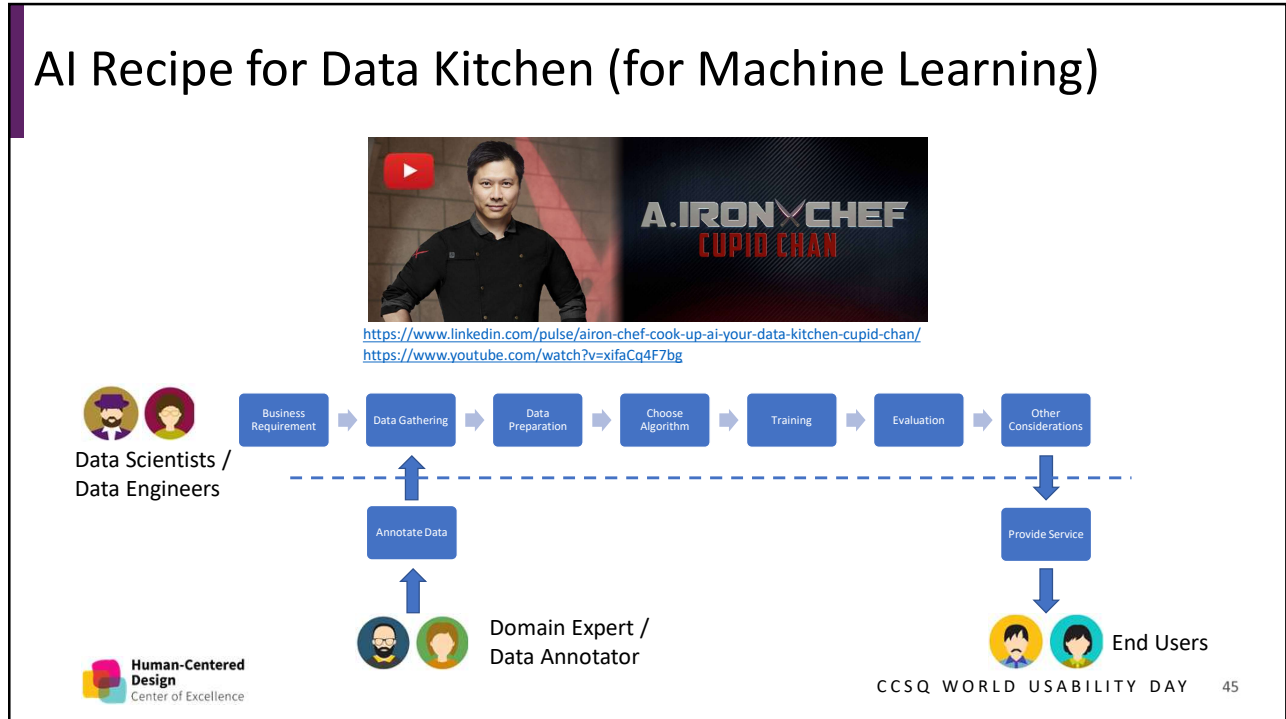
- No need for fraud data
 - No need to manually prepare a mixed training data set, which is usually has a very few fraud data to start with
- Discriminator will take in either real benign or generated malicious
 - More adaptive to different kinds of malicious behavior
- Adapt to newly emerged normal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

43

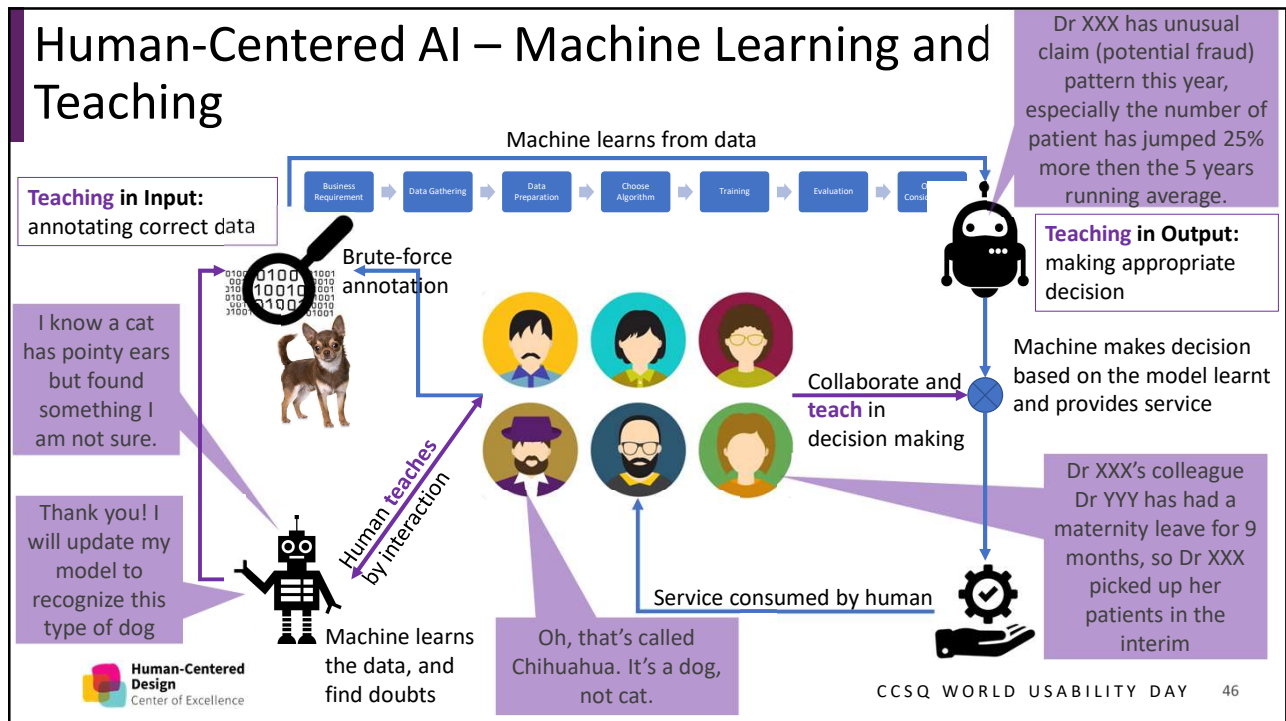
Recap: What we have talked about so far...



44



45



46

47

When you talk about AI, think of IA!

Artificial Intelligence

In Speaker Packet: *There is zero tolerance for sales pitches masquerading as educational or informational.*

VS

Intelligence Augmentation



48

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



49

2017 CONFERENCE ON HEALTH IT AND ANALYTICS (CHITA)



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



FEATURED PANELISTS



... LinkedIn Story continues



50

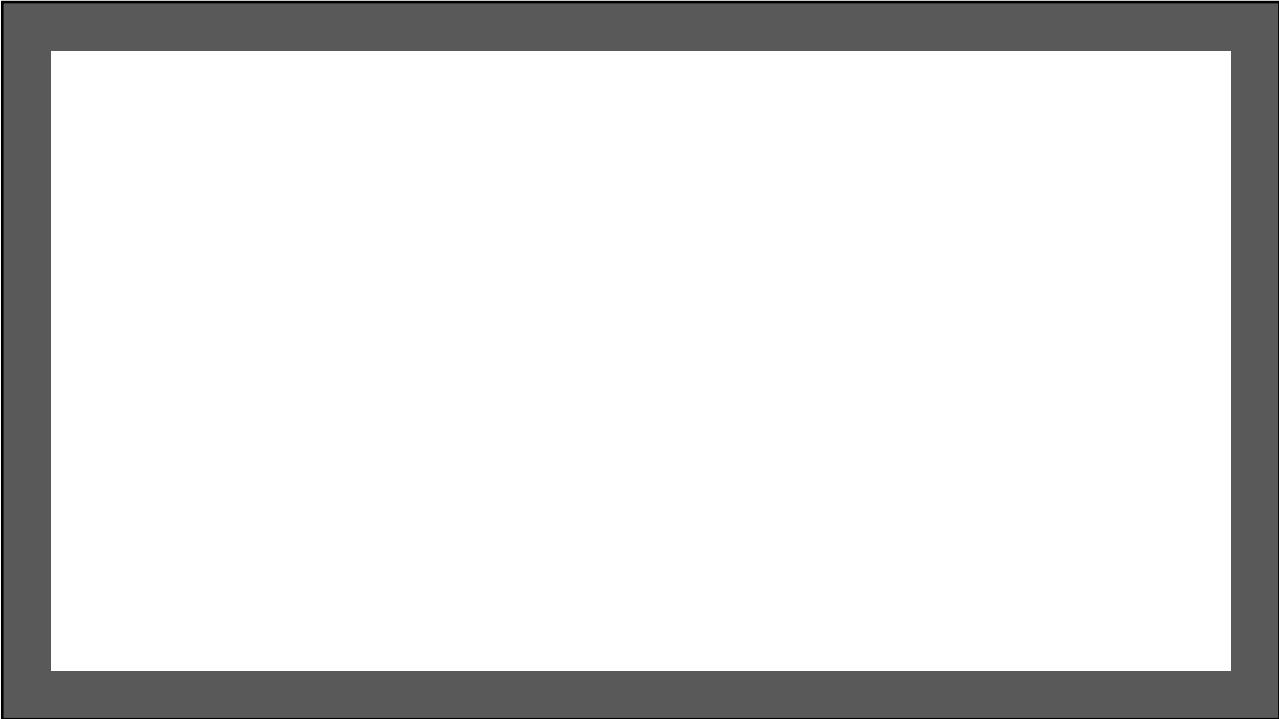
I decided to find my most knowledgeable friend for help

The screenshot shows a Google search for 'jacqueline mars'. The search results include a Wikipedia entry and a Forbes profile. The Wikipedia entry provides biographical information: 'Jacqueline Mars (born October 10, 1939) is an American heiress and investor. She is the daughter of Audrey Ruth (Meyer) and Forrest Mars, Sr., and granddaughter of Frank C. Mars, founders of the American candy company Mars, Incorporated. Education: Miss Hall's School Parent(s): Forrest Mars, Sr. (1904–1999); Audr... Born: October 10, 1939 (age 80) Relatives: Frank C. Mars (grandfather); Forrest ... Career - Personal life'. The Forbes profile states: 'Jacqueline Mars owns an estimated one third of Mars, the world's largest candymaker, founded...'. The Forbes logo and 'Human-Centered Design Center of Excellence' are visible in the bottom left corner of the screenshot. The text 'CCSQ WORLD USABILITY DAY 51' is at the bottom right of the slide.

51

The screenshot shows a text conversation. Cupid Chan (10:29 PM) asks: 'I am sorry, but exactly what?'. Jacqueline Mars (10:31 PM) replies: 'What you do in your place of work and the profitable it is.'. Cupid Chan (10:31 PM) replies: 'i see'. Cupid Chan is typing... Jacqueline Mars (10:38 PM) replies: 'Don't you want to talk to me about it's fine I'm sorry 😊'. Cupid Chan (10:38 PM) replies: '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) replies: 'WOW Cool'.

52




53




54

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



Presented by
Cupid Chan
Anonymous Hacker

Vulnerability
WORLD ~~USABILITY~~ DAY




55

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](https://twitter.com/cupidckchan)



56