Que la Generación Z no rompa tus modelos

Alicia Pérez | PyConEs 2019

STYLESAGE

#drama

Sesgos en la moda

"Si hay algo que caracteriza a la Generación Z es no tener reglas preestablecidas"

La generación Z ya está aquí

THE IRREGULAR REPORT: LA GENERACIÓN Z Y LA FLUIDEZ DE GÉNERO

11 / 01 / 2019

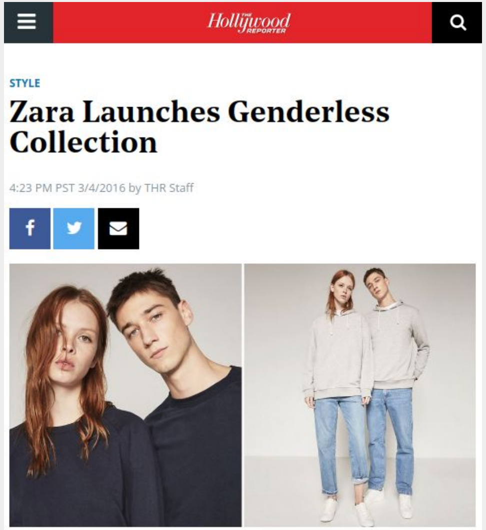
TENDENCIAS

'Genderless', cinco claves para vestir como la generación Z

MODA

Las nuevas generaciones no visten de hombre o mujer; hola a lo neutral

Marcas genderless



Las firmas low cost también se sumaron al fenómeno genderless


¿Están nuestros
modelos preparados?

Concepts

Concept	Probability
groom	100.00%
bride	62.08%
couple	59.37%
wedding	55.31%
man	50.50%
male	41.93%
love	41.12%
marriage	40.93%
dress	39.84%
married	35.54%

PREDICTED CONCEPT	PROBABILITY
groom	1.000
wedding	1.000
bride	0.999
veil	0.981
love	0.980
fashion	0.979
bridal	0.978
dinner jacket	0.978
outdoors	0.970
dress	0.969
engagement	0.968
ceremony	0.962
woman	0.958
marriage	0.955
nature	0.952
romance	0.946
portrait	0.936

Concepts

vestment	69.19%
costume	64.38%
gown	55.59%
clothing	51.32%
outerwear	41.49%
dress	38.84%
fashion	34.68%
portrait	27.17%
culture	26.49%
adult	26.10%

PREDICTED CONCEPT	PROBABILITY
traditional	0.992
kimono	0.983
geisha	0.977
culture	0.972
people	0.971
costume	0.967
woman	0.961
fashion	0.957
girl	0.954
wear	0.953
dress	0.943
portrait	0.942
person	0.932

Concepts

groom	67.19%
costume	40.01%
clothing	39.00%
kimono	38.11%
dress	35.24%
fashion	31.67%
robe	30.27%
adult	26.13%
garment	25.63%
portrait	23.95%

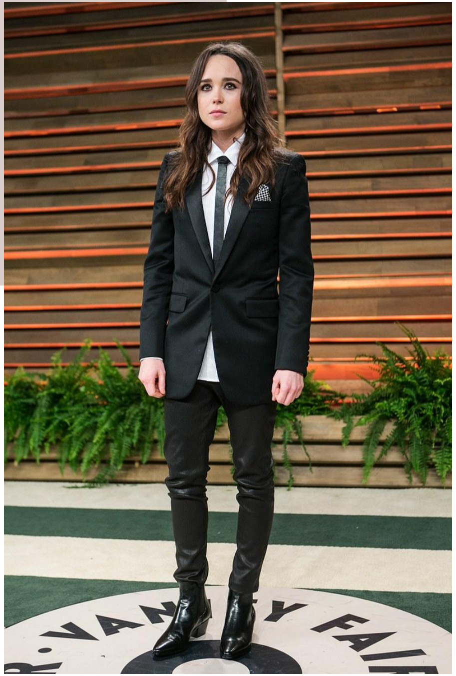
PREDICTED CONCEPT	PROBABILITY
traditional	0.994
woman	0.979
two	0.979
wear	0.977
dress	0.973
wedding	0.973
people	0.968
celebration	0.968
fashion	0.966
girl	0.958
costume	0.955
love	0.951
bride	0.946
family	0.932
Christmas	0.925
beautiful	0.925

Concepts

man	37.65%
person	34.07%
people	30.14%
male	29.86%
adult	25.93%
groom	24.46%
couple	22.66%
happy	19.44%
home	16.76%
smiling	16.65%

kimono	0.988
gown (clothing)	0.964
wear	0.959
people	0.957
woman	0.955
man	0.953
indoors	0.942
adult	0.938
geisha	0.928
portrait	0.927
samurai	0.880
ceremony	0.876
sit	0.861
facial expression	0.860
two	0.848
costume	0.836
movie	0.836
one	0.832

PREDICTED CONCEPT	PROBABILITY
street	0.994
woman	0.991
urban	0.990
outdoors	0.959
fashion	0.958
adolescent	0.954
girl	0.953
city	0.949
wear	0.946
skateboard	0.936
exercise	0.929
lifestyle	0.920
college	0.910
portrait	0.907
young	0.906
casual	0.906
student	0.899
sunglasses	0.897
one	0.885
pretty	0.884



PREDICTED CONCEPT	PROBABILITY
woman	0.954
business	0.943
fashion	0.926
people	0.917
young	0.914
outdoors	0.896
pretty	0.892
one	0.890
portrait	0.888
contemporary	0.873
elegant	0.872
serious	0.859
success	0.847
intelligence	0.832
adult	0.829
looking	0.825
actor	0.812
formal	0.784
man	0.779
achievement	0.771

PREDICTED CONCEPT	PROBABILITY
people	0.985
sunglasses	0.975
one	0.973
street	0.971
urban	0.971
portrait	0.968
fashion	0.959
man	0.959
jacket	0.955
adult	0.927
person	0.919
trendy	0.915
fashionable	0.915
cool	0.910
model	0.905
coat	0.895
style	0.887

PREDICTED CONCEPT	PROBABILITY
man	0.948
street	0.944
people	0.943
military	0.935
outdoors	0.899
portrait	0.897
traditional	0.894
woman	0.889
uniform	0.876
wear	0.876
urban	0.825
parade	0.809
formal	0.800
kilt	0.792
outfit	0.784
girl	0.783

PREDICTED CONCEPT	PROBABILITY
portrait	0.988
people	0.984
adult	0.977
man	0.974
luggage	0.971
wear	0.967
musician	0.954
festival	0.944
music	0.940
woman	0.927
offense	0.922
recreation	0.918

PREDICTED CONCEPT	PROBABILITY
fashion	0.975
man	0.958
isolated	0.954
belt	0.946
wear	0.944
pants	0.923
military	0.897
elegant	0.895
style	0.879
traditional	0.870
one	0.870
woman	0.868
young	0.868
figure	0.868

PREDICTED CONCEPT	PROBABILITY
man	0.975
one	0.969
fashion	0.968
street	0.961
people	0.955
outdoors	0.947
adult	0.924
fine-looking	0.919
woman	0.912
portrait	0.911
sunglasses	0.907
wear	0.896
pants	0.888
sexy	0.882

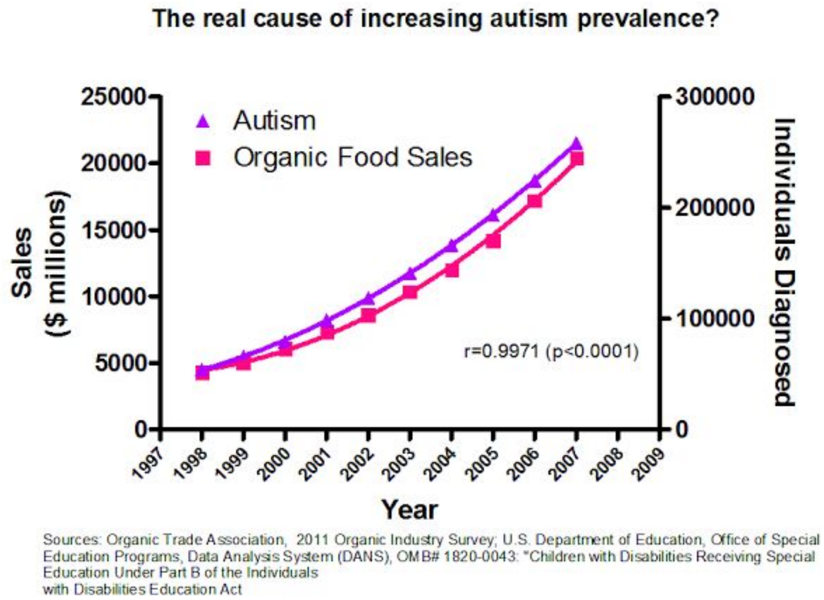
Explicabilidad de los modelos de Machine Learning

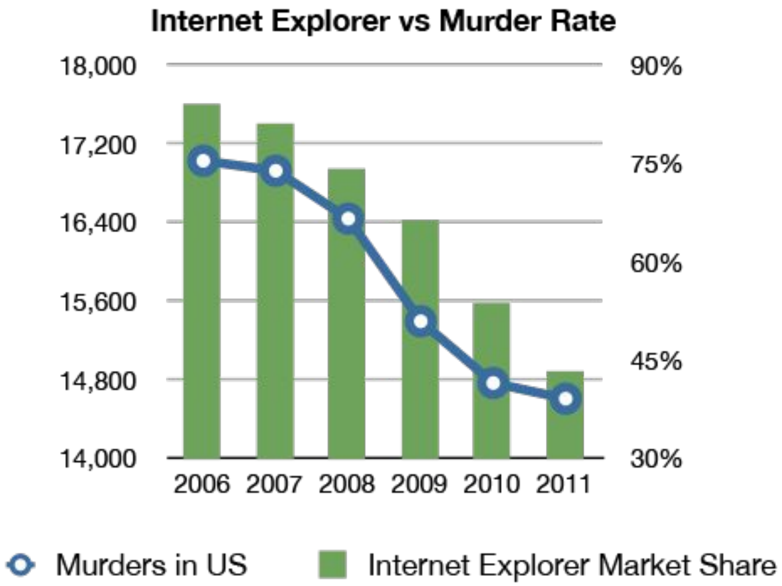
¿En base a qué toman sus decisiones?

Sesgos inconscientes

upworthy.com

Sesgos Inconscientes





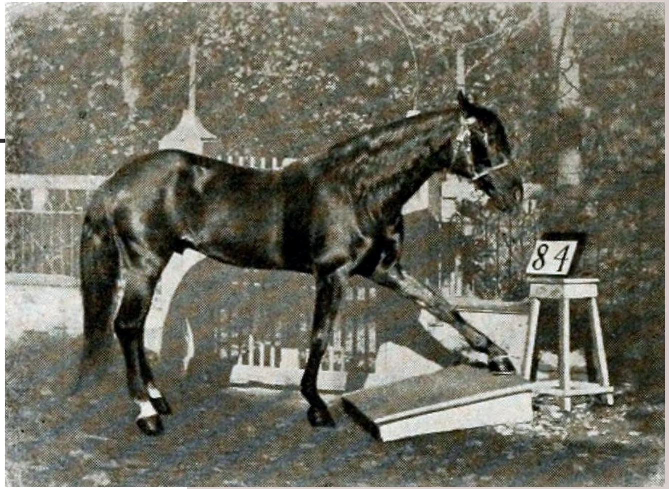
+ de éstas en "Malas Gráficas" de @puratura

futurism.com

Efecto Clever Hans

[...] la posibilidad de que el experimentador "contamine" involuntariamente los resultados del experimento mediante gestos, tonos de voz, lenguaje corporal, etc.

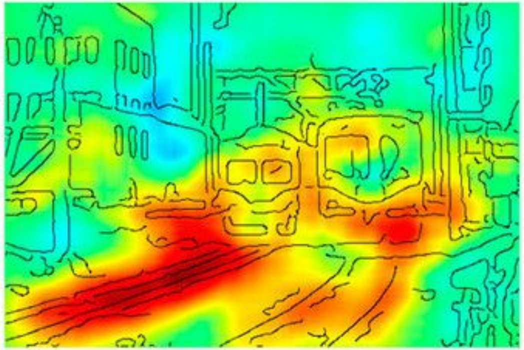
Wikipedia



wikipedia.org


THEN A MIRACLE OCCURS...
s.harris
"I THINK YOU SHOULD BE MORE EXPLICIT HERE IN STEP TWO."

Imágenes de trenes



El algoritmo detectaba los raíles, no los trenes

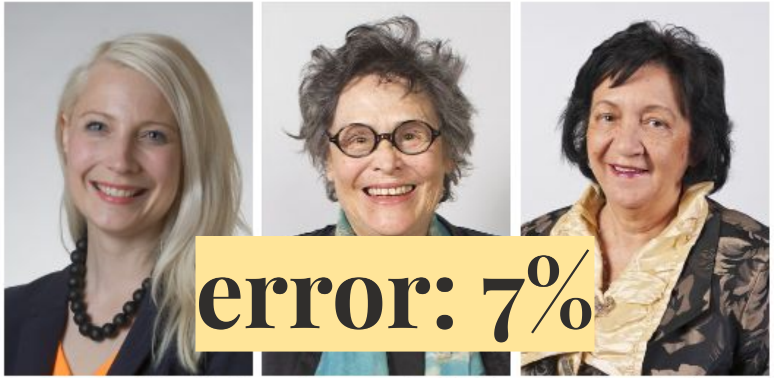
phys.org

Color Matters in Computer Vision

Facial recognition algorithms made by Microsoft, IBM and Face++ were more likely to misidentify the gender of black women than white men.

Gender was misidentified in **up to 1 percent of lighter-skinned males** in a set of 385 photos.

Gender was misidentified in **up to 12 percent of darker-skinned males** in a set of 318 photos.



Gender was misidentified in **up to 7 percent of lighter-skinned females** in a set of 296 photos.

Gender was misidentified in **35 percent of darker-skinned females** in a set of 271 photos.

nytimes.com

≡ EL PAÍS TECNOLOGÍA

La aplicación FaceApp 'blanquea' a los usuarios para hacerlos "más sexys"

Críticas en las redes porque el filtro para parecer más 'sexy' aclara el tono de piel y elimina las gafas de la imagen

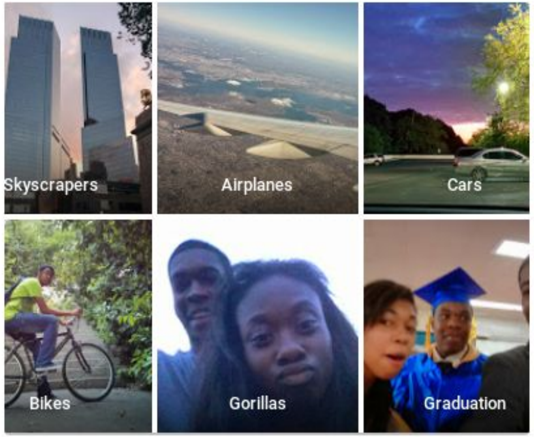
GOOGLE \ TECH \ ARTIFICIAL INTELLIGENCE

Google 'fixed' its racist algorithm by removing gorillas from its image-labeling tech

Nearly three years after the company was called out, it hasn't gone beyond a quick workaround

jackyalcine ➡ SOON TwitchCon 2019
@jackyalcine

Google Photos, y'all fucked up. My friend's not a gorilla.



♡ 2,754 3:22 AM - Jun 29, 2015

3,659 people are talking about this

theverge.com

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TECH \ AMAZON \ ARTIFICIAL INTELLIGENCE

Amazon reportedly scraps internal AI recruiting tool that was biased against women

The secret program penalized applications that contained the word "women's"

By James Vincent | Oct 10, 2018, 7:09am EDT

July 07, 2015

Questioning the Fairness of Targeting Ads Online

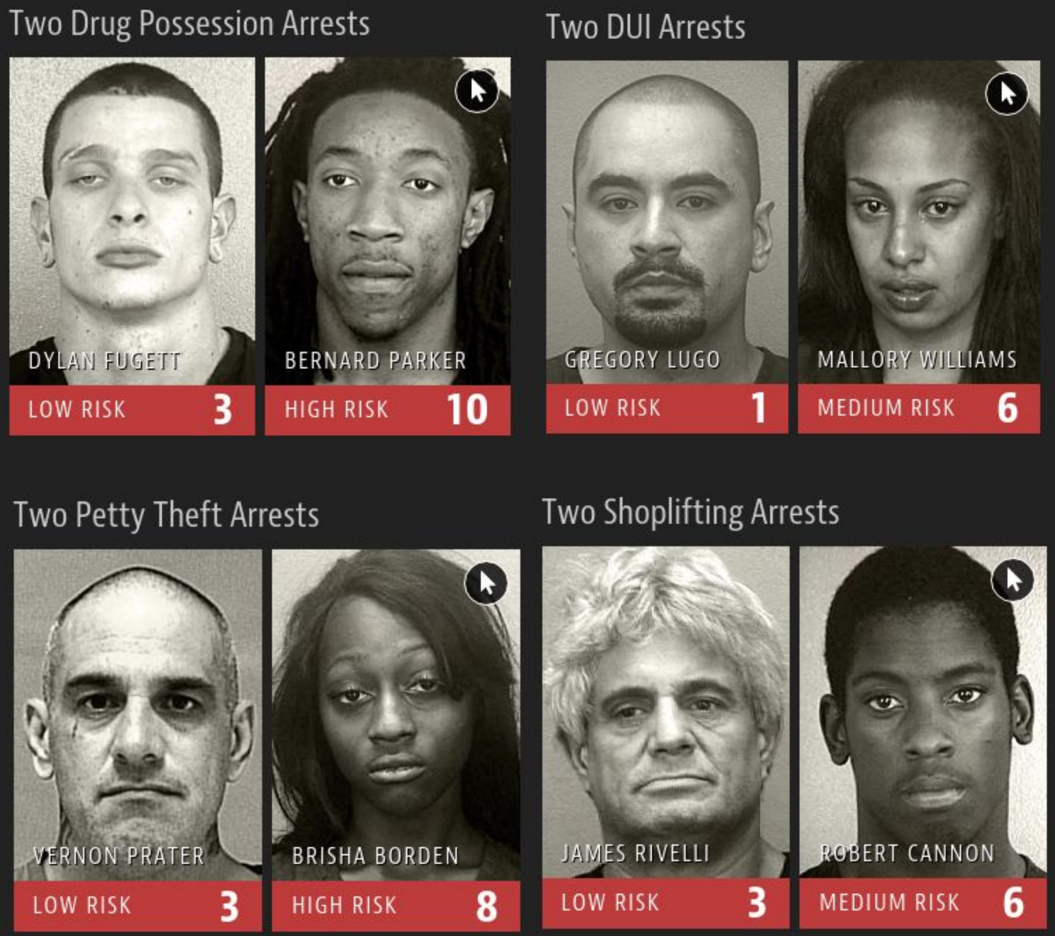
Top ads for identifying the female group

Ad Title	Ad URL	Times shown to Females	Times shown to Males
Jobs (Hiring Now)	www.jobsinyourarea.co	45	8
4Runner Parts Service	www.westernpatoyotaservice.com	36	5
Criminal Justice Program	www3.mc3.edu/Criminal+Justice	29	1
Goodwill - Hiring	goodwill.careerboutique.com	121	39
UMUC Cyber Training	www.umuc.edu/cybersecuritytraining	38	30

Top ads for identifying the male group

Ad Title	Ad URL	Times shown to Females	Times shown to Males
$200k+ Jobs - Execs Only	careerchange.com	311	1816
Find Next $200k+ Job	careerchange.com	7	36
Become a Youth Counselor	www.youthcounseling.degreeleap.com	0	310
CDL-A OTR Trucking Jobs	www.tadrivers.com/OTRJobs	0	8
Free Resume Templates	resume-templates.resume-now.com	8	10

Prodata
vs
Compas



propublica.org

Cómo combatir los sesgos

Técnicas y herramientas en Python

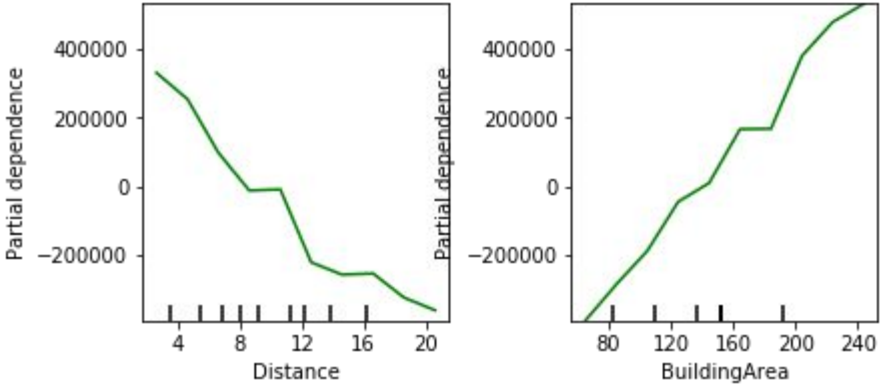
Técnicas de Interpretación de modelos

Permutation Importance

Height at age 20 (cm)	Height at age 10 (cm)	...	Socks owned at age 10
182	155	...	20
175	147	...	10
...	...	...	...
156	142	...	8
153	130	...	24

Height at age 20 (cm)	Height at age 10 (cm)	...	Socks owned at age 10
182	155	...	20
175	147	...	10
...	...	...	...
156	142	...	8
153	130	...	24

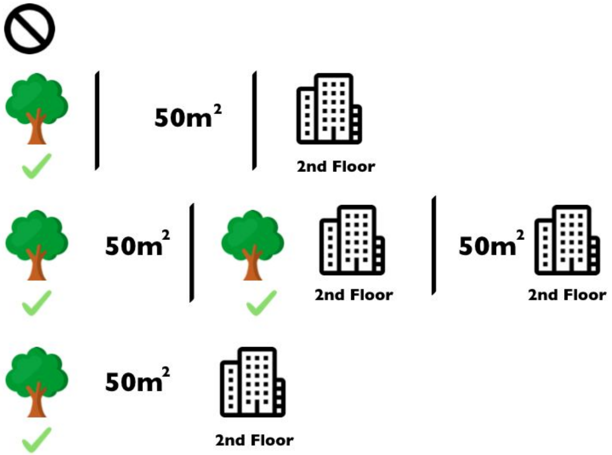
Partial Dependence Plots (PDP)



kaggle.com

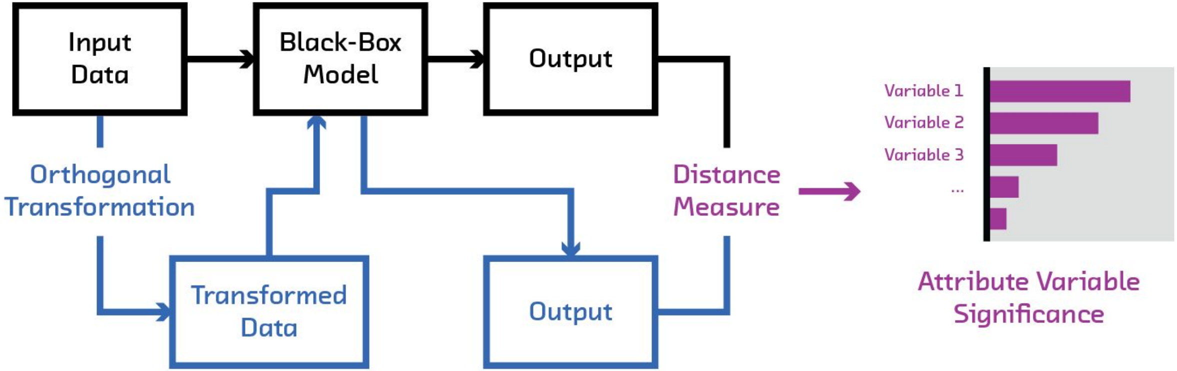
SHAP Values

SHapley
Additive
ex**P**lanations



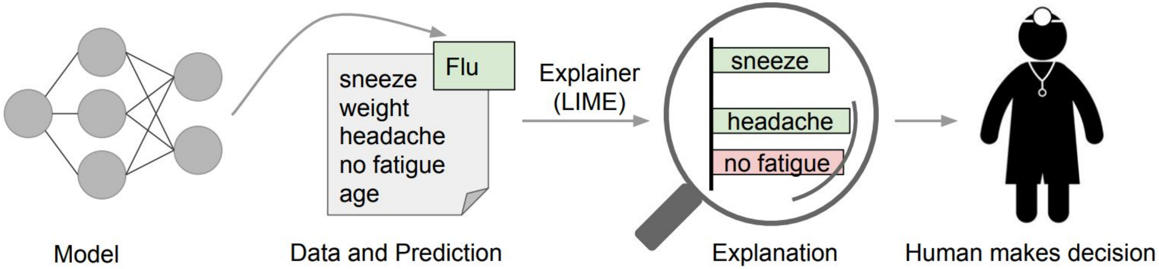
Herramientas en Python

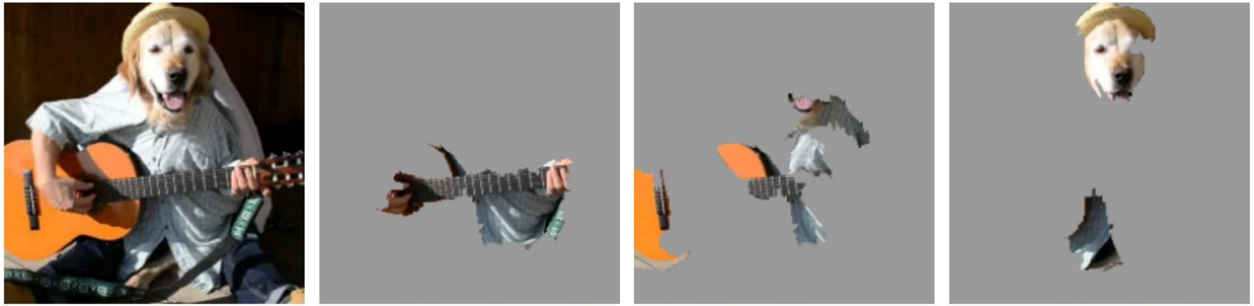
FairML



blog.fastforwardlabs.com

lime



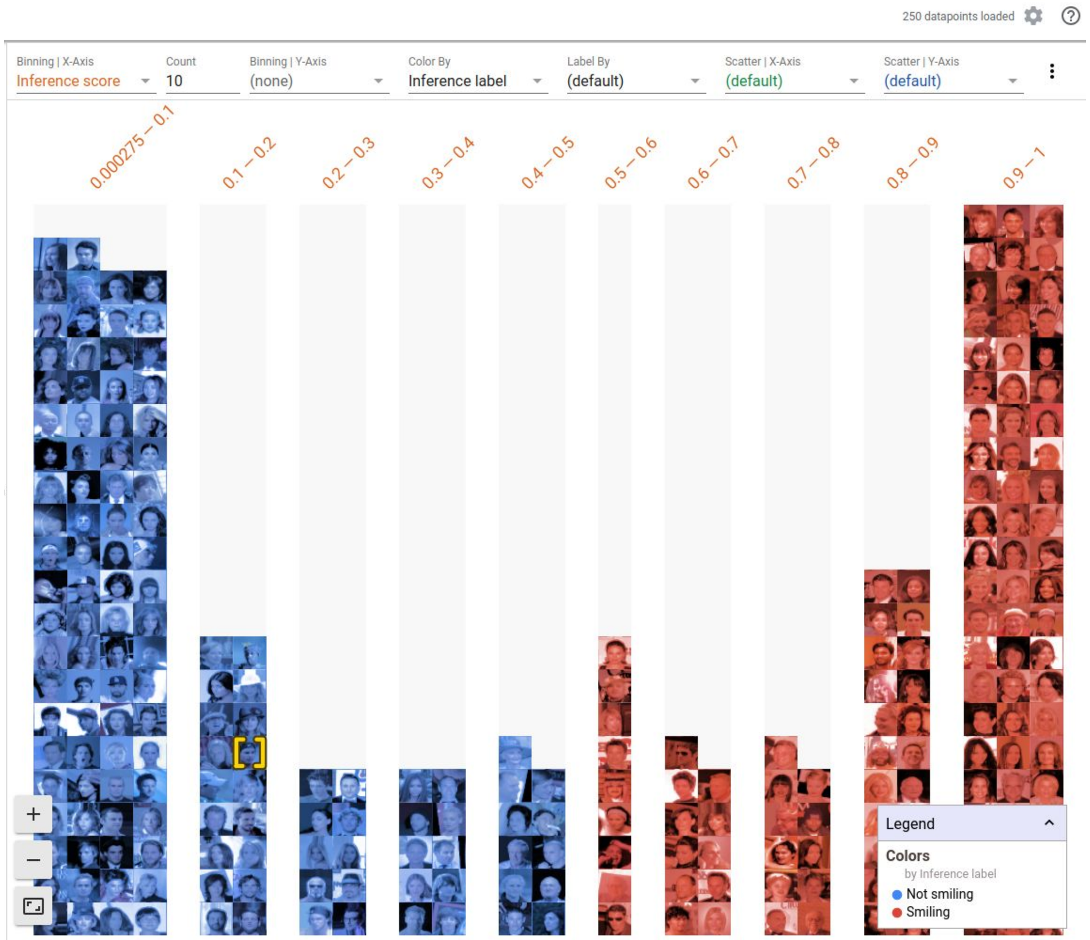


(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

Figure 4: Explaining an image classification prediction made by Google's Inception neural network. The top 3 classes predicted are "Electric Guitar" ($p = 0.32$), "Acoustic guitar" ($p = 0.24$) and "Labrador" ($p = 0.21$)

arxiv.org

What-If Dashboard



pair-code.github.io

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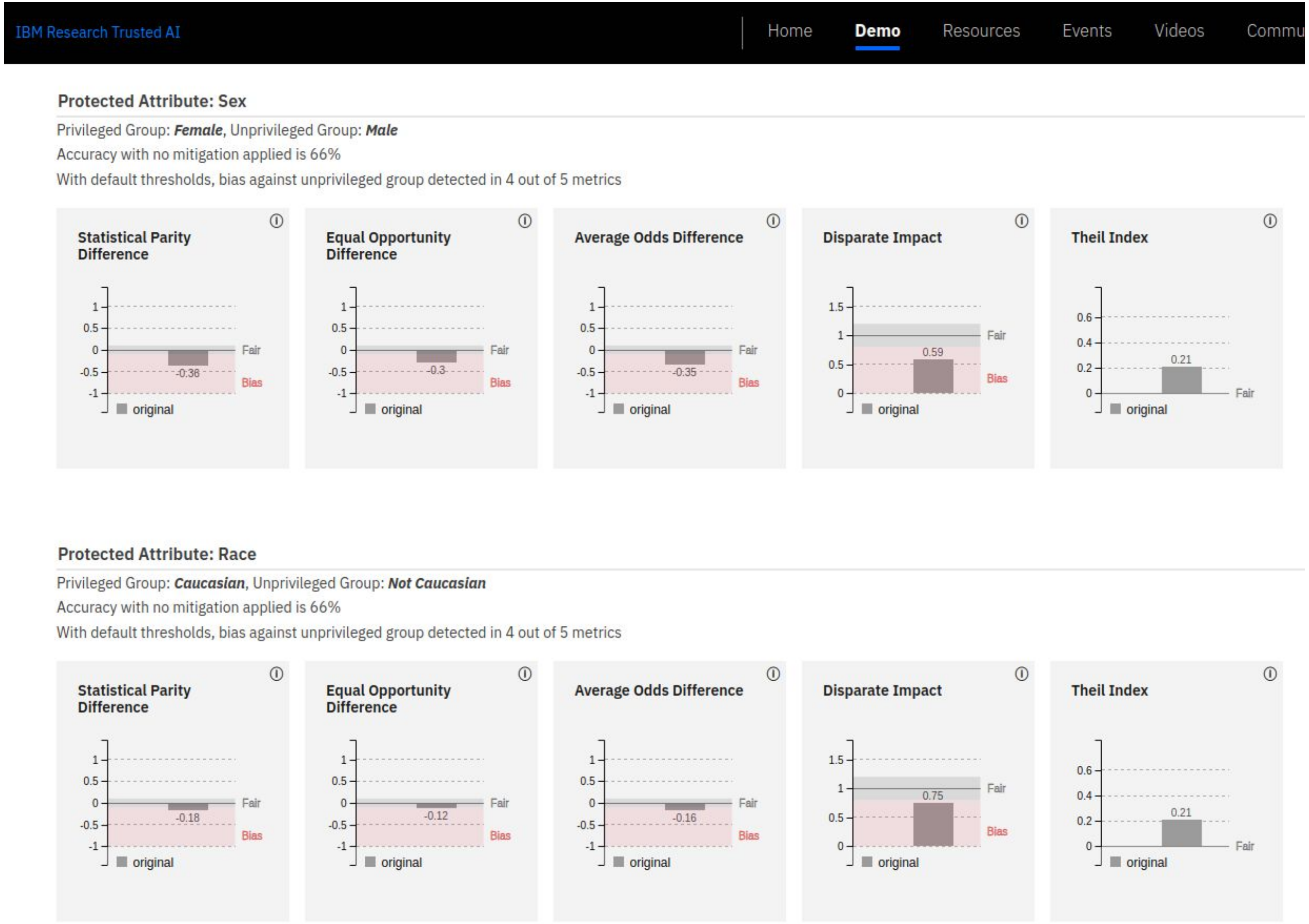
IBM AI Fairness 360



aif360.mybluemix.net


Demo
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En resumen...

Sesgos

Los datos introducen sesgos en nuestros modelos

Moda

Los modelos tienen sesgos que debemos corregir para que en un corto plazo no queden deprecados

Métodos en Python

Ej. permutation importance & PDP

Herramientas

Ej. FairML, lime, What-IF, IBM AIF 360

Que la Generación Z no rompa tus modelos

¡Gracias!

alicia@stylesage.co

https://github.com/aliciapj/ml_bias

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