La desinformación
desde el análisis computacional del discurso

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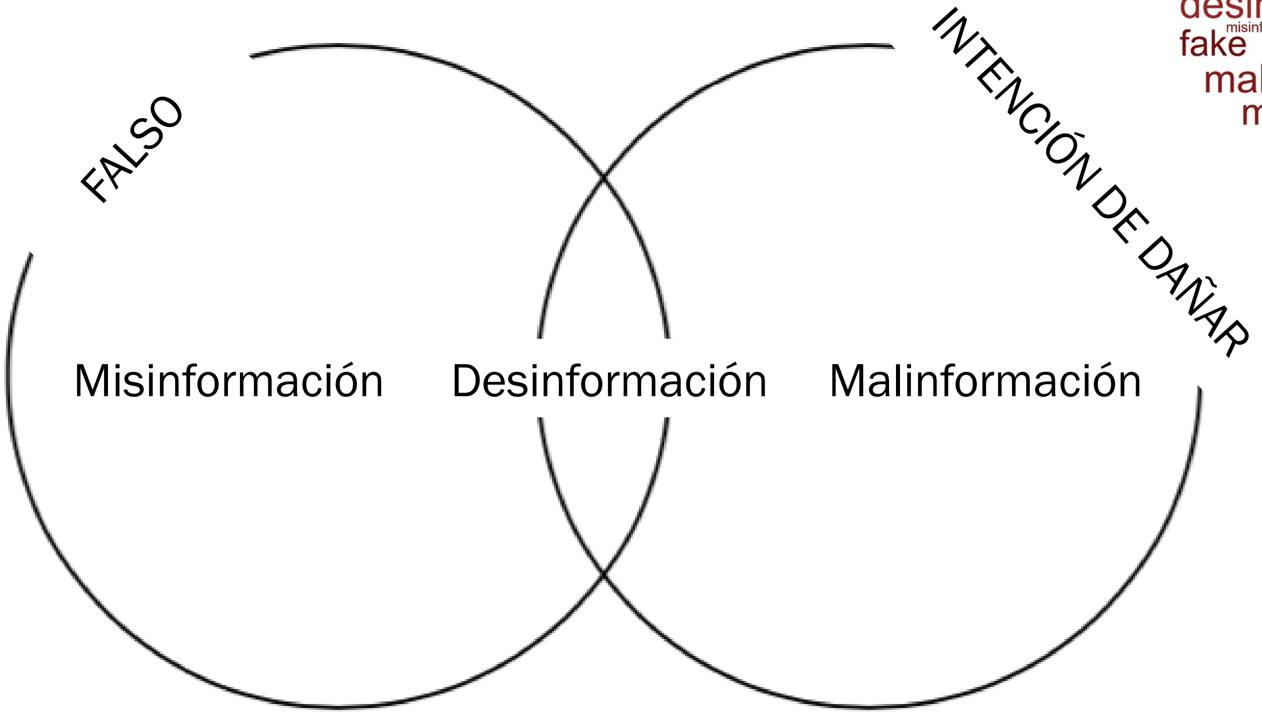
Jornadas “La lingüística frente a la amenaza de la desinformación”
Universidad de Navarra
27 mayo 2024

Discourse Processing Lab

SFU SIMON FRASER UNIVERSITY
ENGAGING THE WORLD

Trastornos de la información



https://firstdraftnews.org/long-form-article/understanding-information-disorder/

El puzle de la desinformación

Inteligencia artificial y análisis del lenguaje

1
Educación

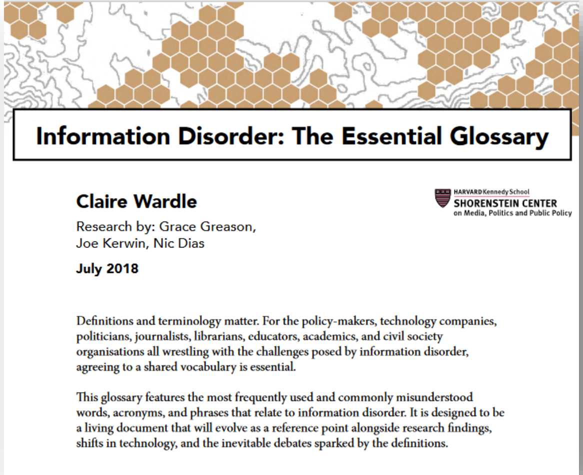
2
Parar la propagación

3
Verificación experta de datos

4
Verificación automática

Investigación dentro de las ciencias sociales

Definiciones


Information Disorder: The Essential Glossary

Claire Wardle

HARVARD Kennedy School SHORENSTEIN CENTER on Media, Politics and Public Policy

Research by: Grace Greason, Joe Kerwin, Nic Dias

July 2018

Definitions and terminology matter. For the policy-makers, technology companies, politicians, journalists, librarians, educators, academics, and civil society organisations all wrestling with the challenges posed by information disorder, agreeing to a shared vocabulary is essential.

This glossary features the most frequently used and commonly misunderstood words, acronyms, and phrases that relate to information disorder. It is designed to be a living document that will evolve as a reference point alongside research findings, shifts in technology, and the inevitable debates sparked by the definitions.

Propagación


RESEARCH

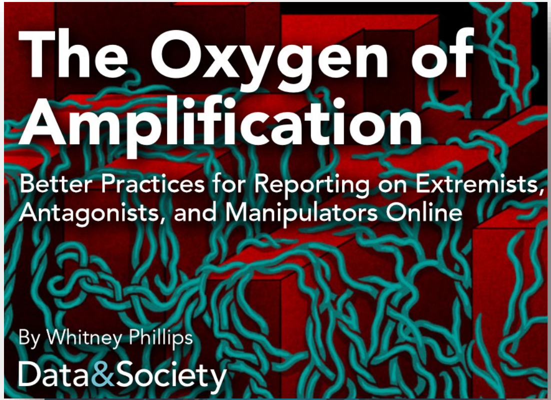
SOCIAL SCIENCE

The spread of true and false news online

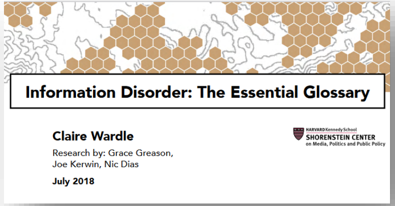
Soroush Vosoughi,[1] Deb Roy,[1] Sinan Aral[2]*

We investigated the differential diffusion of all of the verified true and false news stories distributed on Twitter from 2006 to 2017. The data comprise ~126,000 stories tweeted by ~3 million people more than 4.5 million times. We classified news as true or false using information from six independent fact-checking organizations that exhibited 95 to 98% agreement on the classifications. Falsehood diffused significantly farther, faster, deeper, and more broadly than the truth in all categories of information, and the effects were more pronounced for false political news than for false news about terrorism, natural disasters, science, urban legends, or financial information. We found that false news was more novel than true news, which suggests that people were more likely to share novel information. Whereas false stories inspired fear, disgust, and surprise in replies, true stories inspired anticipation, sadness, joy, and trust. Contrary to conventional wisdom, robots accelerated the spread of true and false news at the same rate, implying that false news spreads more than the truth because humans, not robots, are more likely to spread it.

Verificación y amplificación



Investigación: Definiciones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MALDITO BULO

- Bulo
  - Datos, hechos, imágenes
  - Contrastados que son falsos o manipulados
  - Sacados fuera de contexto
  - Satíricos, presentados como reales
- No hay pruebas
  - No se sabe si son ciertos

CHEQUEADO

- Inchequeable
- Verdadero
- Verdadero, pero…
- Discutible
- Apresurado
- Exagerado
- Engañoso
- Insostenible
- Falso

Investigación: Propagación

RESEARCH

SOCIAL SCIENCE

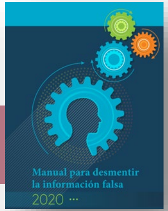
The spread of true and false news online

Soroush Vosoughi,[1] Deb Roy,[1] Sinan Aral[2*]

LAS NOTICIAS FALSAS SON MÁS VIRALES

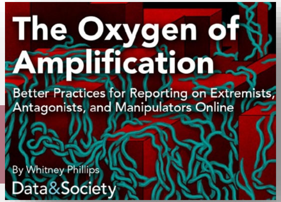
- Las noticias falsas y la desinformación
- También las noticias satíricas
  - Se propagan más rápidamente
  - Llegan a más gente

Investigación: Verificación y amplificación



VERIFICACIÓN

- Herramienta importante
  - Precisa de expertas
  - Política, economía, salud, cambio climático…
- Cuidado con el método
  - Para los desmentidos
  - Métodos basados en psicología cognitiva
  - El bocadillo de la verdad



AMPLIFICACIÓN

- Cuidado con amplificar las noticias
- A veces la verificación o la discusión en los medios simplemente difunde la noticia falsa más
- Manipulación: globos sonda
- Psicología cognitiva
  - Nos acordamos de la noticia
  - ¡No si de era falsa o no!

Un problema social

NO ES INDIVIDUAL

- No lo podemos resolver como individuos
- Necesitamos de las instituciones
  - Educación
  - Regulación de los medios y las plataformas digitales

NO ES IGUAL PARA TODAS

- La desinformación afecta desproporcionadamente a ciertos colectivos
  - Mujeres
  - Inmigrantes
  - Grupos minoritarios
  - Periodistas
  - Activistas

El puzle de la desinformación

Inteligencia artificial y análisis del lenguaje

1
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4
Verificación automática

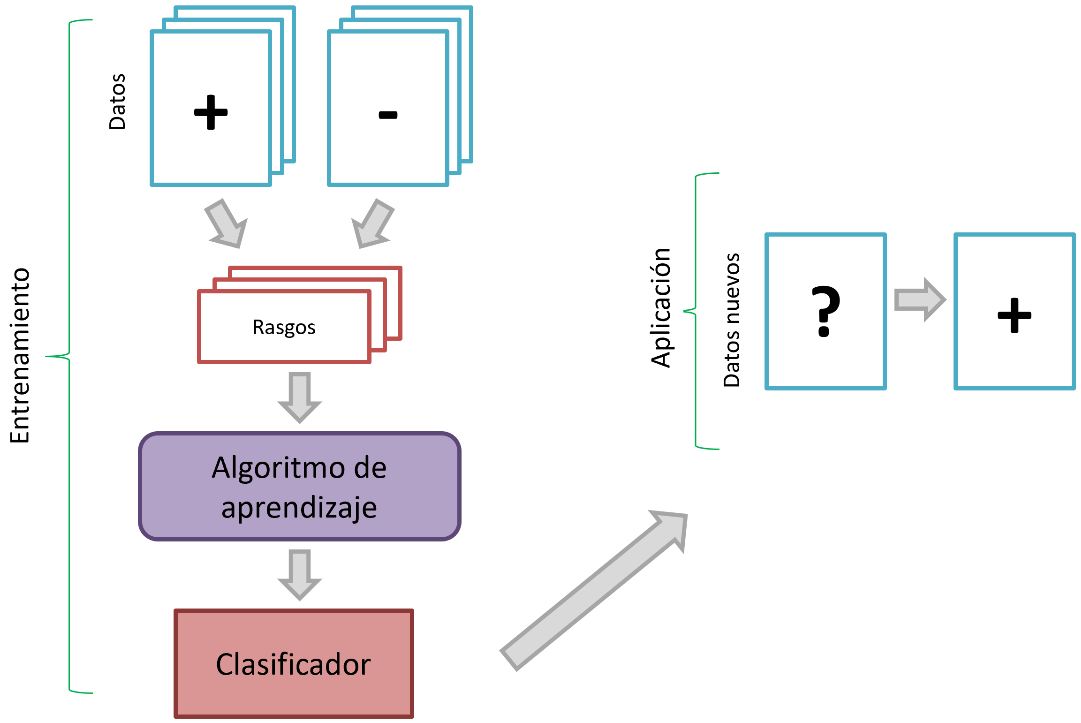
4. INTELIGENCIA ARTIFICIAL Y ANÁLISIS DEL LENGUAJE

- Hipótesis
  - El lenguaje de las noticias falsas es diferente
  - Hay rasgos que las identifican
  - Independientemente de la distribución, el sesgo, etc.

- Propuesta
  - Podemos desarrollar un sistema que detecte las noticias falsas usando rasgos lingüísticos

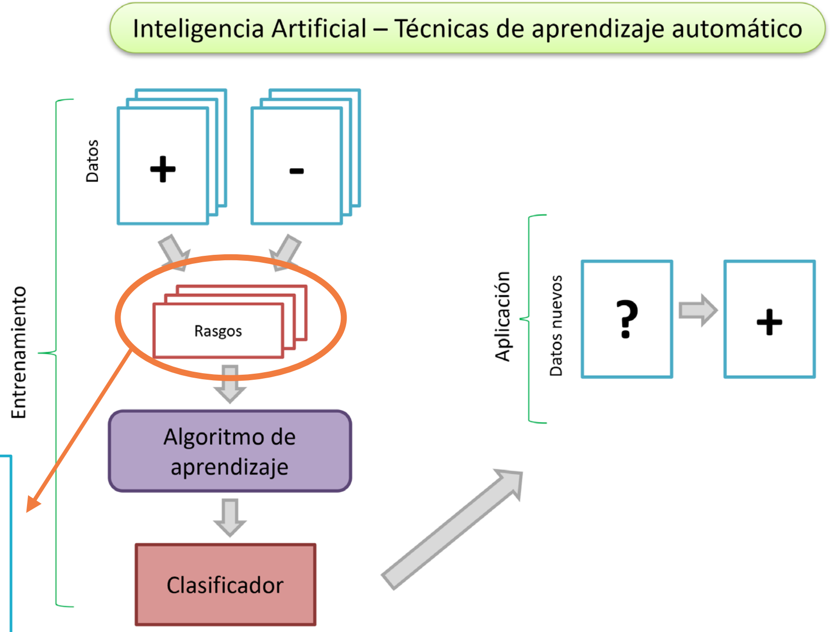
- Técnicas
  - Inteligencia artificial, aprendizaje automático
  - Procesamiento del lenguaje natural

Inteligencia Artificial – Técnicas de aprendizaje automático



PROCESAMIENTO DEL LENGUAJE NATURAL

- Campo que solapa la informática, la inteligencia artificial y la lingüística
- Extracción de información lingüística para diferentes aplicaciones
  - Reconocimiento de entidades
  - Búsqueda y recuperación de información
  - Resumen automático
  - Traducción automática
  - Análisis de la opinion
  - …



Nuestro proyecto

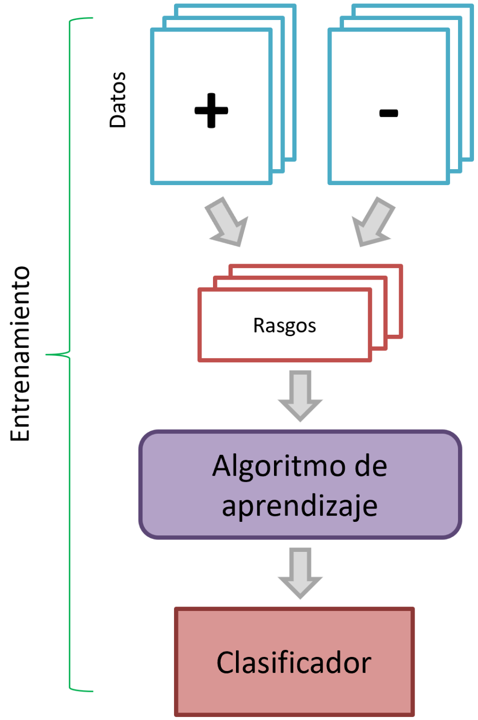
- Hipótesis
  - El lenguaje de las noticias falsas es diferente del lenguaje de las noticias contrastadas
- Métodos
  - Aprendizaje automático, PLN
  - Lingüística de corpus
  - Análisis multidimensional (Biber 1995)
    - Análisis de la variación lingüística en el texto

Fatemeh Torabi Asr

Biber, D. (1995). *Dimensions of Register Variation: A Cross-Linguistic Comparison*. Cambridge University Press.

El aprendizaje automático necesita datos

- Los métodos actuales de aprendizaje automático utilizan grandes cantidades de datos
  - Aprendizaje supervisado
  - Input: corpus con etiquetas (spam/no_spam)
  - Output: un clasificador que diferencia esos dos tipos de textos en el corpus



Los datos

- La desinformación y las noticias falsas son un problema
- Son un problema de big data
- Los estamos solucionando con ‘small data’

Big Data and quality data for fake news and misinformation detection

Big Data & Society
January–June 2019: 1–14
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sagepub.com/journals-permissions
DOI: 10.1177/2053951719843310
journals.sagepub.com/home/bds
SAGE

Fatemeh Torabi Asr and Maite Taboada

Abstract
Fake news has become an important topic of research in a variety of disciplines including linguistics and computer science. In this paper, we explain how the problem is approached from the perspective of natural language processing, with the goal of building a system to automatically detect misinformation in news. The main challenge in this line of research is collecting quality data, i.e., instances of fake and real news articles on a balanced distribution of topics. We review available datasets and introduce the MisInfoText repository as a contribution of our lab to the community. We make available the full text of the news articles, together with veracity labels previously assigned based on manual assessment of the articles’ truth content. We also perform a topic modelling experiment to elaborate on the gaps and sources of imbalance in currently available datasets to guide future efforts. We appeal to the community to collect more data and to make it available for research purposes.

¿De dónde vienen los datos?

- Necesitamos dos tipos de datos
  - Ejemplos positivos (spam, noticias falsas)
  - Ejemplos negativos (no_spam, noticias contrastadas)

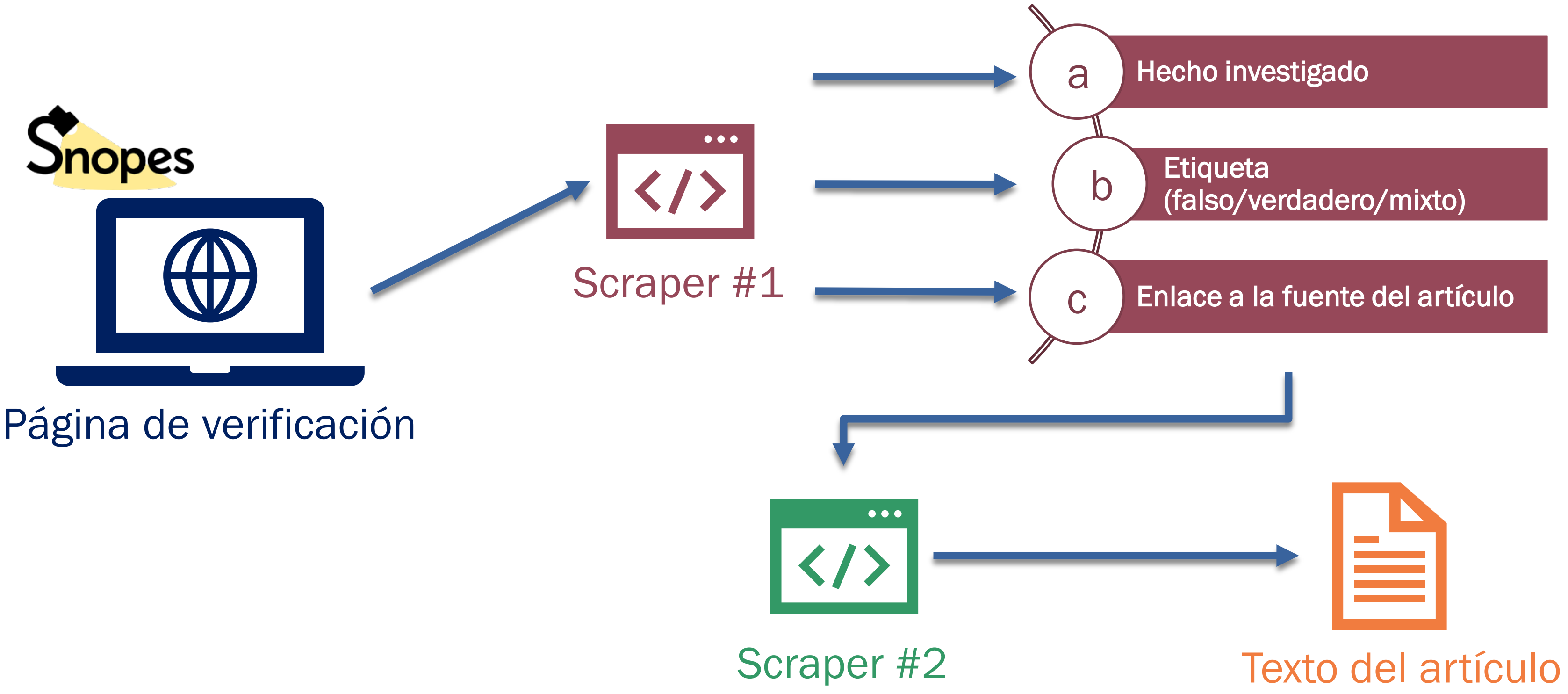
- Problemas
- Ruido
  - bulosynoticias.net igual reproduce noticias de medios fiables
- Sesgo
  - A mí me parece que bulosynoticias.net publica noticias falsas
- Necesitamos
  - Artículos contrastados, uno a uno, por expertas

http://bulosynoticias.net	http://noticiascontrastadas.es
+	-

Artículos de verificadores de datos

- Fuentes
  - Buzzfeed – lista de las top noticias falsas del año
  - Artículos en Snopes, Politifact y Emergent
  - Cada uno, etiquetado individualmente
    - Falso/auténtico

Proceso de recopilación de datos



Fact Checks › Food

Did a Woman Open Fire at McDonald's for Forgetting Bacon on Her Burgers?

hecho investigado

Adds new meaning to the definition of hangry.

By Madison Dapcevich
Published 6 June 2021

Image via Christoph Schmidt/picture alliance via Getty Images

etiqueta

Claim

A Michigan woman was sentenced to up to seven years in prison for opening fire at a McDonald's restaurant after workers forgot to put bacon on her burgers.

Rating

True
About this rating

¿enlace a la fuente?

¿enlace a la fuente?

¿enlace a la fuente?

Origin

A Michigan woman was sentenced to three to seven years in prison after opening fire in 2014 at a McDonald's restaurant where workers twice forgot to put bacon on her burgers during one visit.

Shaneka Torres, who was 30 at the time of her 2015 sentencing, reportedly became angry after the burger she ordered came without the requested bacon. She was offered a free meal by the restaurant, but bacon was left out of the second order, as well. That's when she fired a shot through the drive-thru window, according to The Associated Press. No one was injured.

The case went viral again in May 2021 when TikTok user Tanner Lane shared the story to the social media platform:

Following Torres' arrest, Time reported that the woman was arrested at her home about 30 minutes after the 3 a.m. shooting on Feb. 10, 2014. Her defense attorney argued that Torres discharged the weapon by accident, and that that the incident was not correlated with the burger mishap.

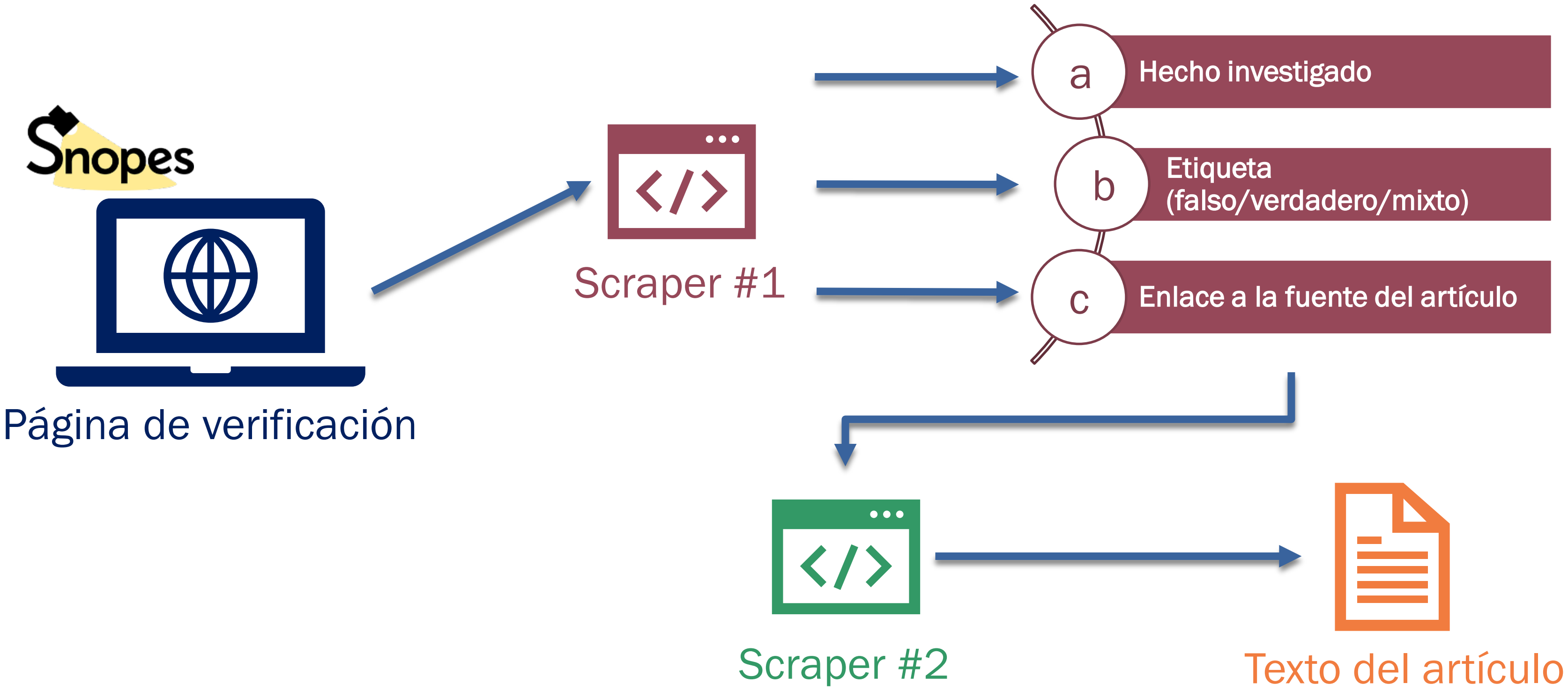
The jury in her trial reportedly deliberated for one hour before finding her guilty of carrying a concealed weapon, discharging a firearm into a building, and felony use of a firearm. The news website Michigan Live reported that Torres was also ordered to stay away from all McDonald's restaurants, but that it was at the discretion of the Michigan Department of Corrections to decide if the ban should continue after her prison release.

Snopes submitted a request to Kent County Circuit Court, the jurisdiction that convicted Torres, for more information surrounding the details of her arrest and subsequent sentencing. We did not hear back in time for publication but will update the article if we do.

By Madison Dapcevich
Published 6 June 2021

https://www.snopes.com/fact-check/woman-opens-fire-at-mcdonalds/

Proceso de recopilación de datos



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The case went viral again in May 2021 when TikTok user Tanner Lane shared the story to the social media platform:

Woman gets 3-7-years for shooting over bacon-less burger

April 21, 2015

Click to copy

RELATED TOPICS

Shootings
Lifestyle
Business
Crime
Food and drink
Violent crime
General news

GRAND RAPIDS, Mich. (AP) — A Michigan woman has been sentenced to three to seven years in prison for opening fire at a McDonald's restaurant after workers twice failed to put bacon on her burgers.

Authorities say 30-year-old Shaneka Torres became angry in February 2014 when the first burger she ordered at the restaurant's drive-up station was missing bacon. She was offered a free meal, but bacon also wasn't added to a second burger order.

Police say she fired a shot through the restaurant. No one was injured.

A Kent County Circuit Court jury convicted her March 25. Judge Paul Sullivan on Tuesday sentenced her to one to five years for shooting at a building, plus two years for possessing a firearm during a felony.

Torres says she's sorry "but it's over and done with."

https://apnews.com/article/64f5dd3baa2942548a7eb210806c5d56

Fase 1 (Snopes/Politifact)

Fase 2 (páginas externas)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	politifact_url_phase1	fact_tag_phase1	article_title_phase1	article_claim_phase1	article_claim_citation_phase1	article_published_date_phase1	article_researched_by_phase1	article_edited_by_phase1	article_categories_phase1	original_url_phase1	page_is_first_citation_phase1	error_phase2	original_article_text_phase2	article_title_phase2	publish_date_phase2	author_phase2
2	http://www.p	Half-True	Georgia gas t	"Contrary to	â€" E. Frank S	Wednesday,	April Hunt	Jim Tharpe	Gas Prices, Ta	http://www.g	TRUE	No Error	By Clay G. Co	Georgia Gas T	2011-08-13	
3	http://www.p	TRUE	Health insura	If you "alreac	â€" Barack O	Wednesday,	Angie Drobni	Bill Adair	Health Care	http://frweb	TRUE	No Error	Congressiona	Browse Congressional Bills		
4	http://www.p	TRUE	Analyst says	"Switzerland	â€" Matt Mil	Wednesday,	Louis Jacobsc	Bill Adair	Health Care	http://www.v	TRUE	No Error	A dangerous	Why the Pub	2005-09-06	Matt Miller
5	http://www.p	Pants on Fire	Gov. Jan Brev	"Our law enf	â€" Jan Brew	Wednesday,	Robert Farley	Martha M. H	Immigration	http://www.a	TRUE	No Error	In an exclusiv	Brewer wants	2006-06-24	Brahm Resnik
6	http://www.p	Mostly False	Obama says I	John Boehne	â€" Barack O	Wednesday,	Angie Drobni	Martha M. H	Economy, Ed	http://www.v	TRUE	No Error	2:11 P.M. CD	Remarks by t	2006-09-05	
7	http://www.p	FALSE	Congressiona	"Close to 30%	â€" Daniel M	Wednesday,	Cary Spivak	Greg Borows	Immigration	http://www.c	TRUE	No Error	Greetings, Be	Mielke For Congress		
8	http://www.p	Mostly True	Hillary Clinto	Says Donald T	â€" Hillary Cl	Wednesday,	Jon Greenbe	Katie Sanders	Foreign Polic	http://www.n	TRUE	No Error	Who is bette	Commander-	2012-09-07	Years Ago
9	http://www.p	Mostly True	Do girls make	Young wome	â€" Justin Tru	Wednesday,	Joseph Cariz	Aaron Sharo	Public Health	https://africa	TRUE	No Error	Despite signi	Are 74% of African girls aged 15 to 24 HIV+? I		
10	http://www.p	FALSE	Trump repea	"I was totally	â€" Donald T	Wednesday,	Lauren Carro	Katie Sanders	Iraq	http://www.n	TRUE	No Error	Donald Trum	Trump Respo	2012-02-20	
11	http://www.p	TRUE	Sen. Rob Por	Says the fede	â€" Rob Port	Wednesday,	Tom Feran	Robert Higgs	Energy	http://www.t	TRUE	No Error	The national	Toledo can le	2007-08-27	
12	http://www.p	Half-True	Did Republica	"Republicans	â€" SEIU on	Wednesday,	Angie Drobni	Martha M. H	Corporations	http://thoma	TRUE	No Error	Array (=> 20	H.R.1586 - 111th Congress		Rangel
13	http://www.p	Half-True	Sid Miller: Po	Says a poll sh	â€" Sid Miller	Wednesday,	W. Gardner S	John Bridges	History, Polls	http://www.n	TRUE	No Error	As Austin off	Efforts underway in large T		Johnathan Silver -
14	http://www.p	Half-True	Jeff Denham	Says Barack O	â€" Jeff Denh	Wednesday,	Chris Nichols	Gregory Favr	Homeland Se	http://www.n	TRUE	No Error	Denham: Pro	Denham: Pro	2013-09-04	
15	http://www.p	Mostly False	In Milwaukee	"In 1986, Pre	â€" Donald T	Wednesday,	Tom Kertsche	Greg Borows	Corporations	http://www.j	TRUE	No Error	CLOSE Presid	Trump: We m	2013-09-02	Donald Trump
16	http://www.p	Mostly True	Diana DeGett	Women "rece	â€" Diana De	Wednesday,	Louis Jacobsc	Angie Drobni	Jobs, Women	http://thoma	TRUE	No Error	Senate Comm	S.181 - 111th Congress (20		Mikulski
17	http://www.p	Pants on Fire	Wasserman S	Says she was	â€" Debbie W	Wednesday,	Amy Sherma	Angie Drobni	Israel	http://m.was	TRUE	No Error	Its the messa	Jewish Demo	2008-09-02	Brendan Smialows
18	http://www.p	TRUE	Chris Christie	Says Bruce Sp	â€" Chris Chr	Wednesday,	Bill Wichert	Caryn Shinsk	Pop Culture	http://www.y	TRUE	Not a news a	Published on Sep 5, 2012 Late Night with Jimmy Fallon. Se			

Politifact-Snopes-early-late-sample.xlsx

Verificación manual

- Para cada enlace que pensamos contiene el artículo:
- Fase 1
  - El artículo del verificador y el enlace que estamos contemplando
- Fase 2
  - La página externa
    - ¿Existe todavía?
    - ¿Se refiere al evento investigado?
    - ¿Hemos extraído el texto correctamente?

Crowdsourcing

- Después de esta fase, teníamos 2,000 artículos
  - Validación manual
  - Comprobar el enlace
  - Comprobar que el enlace se refiere a la noticia en Snopes

- Mediante crowdsourcing

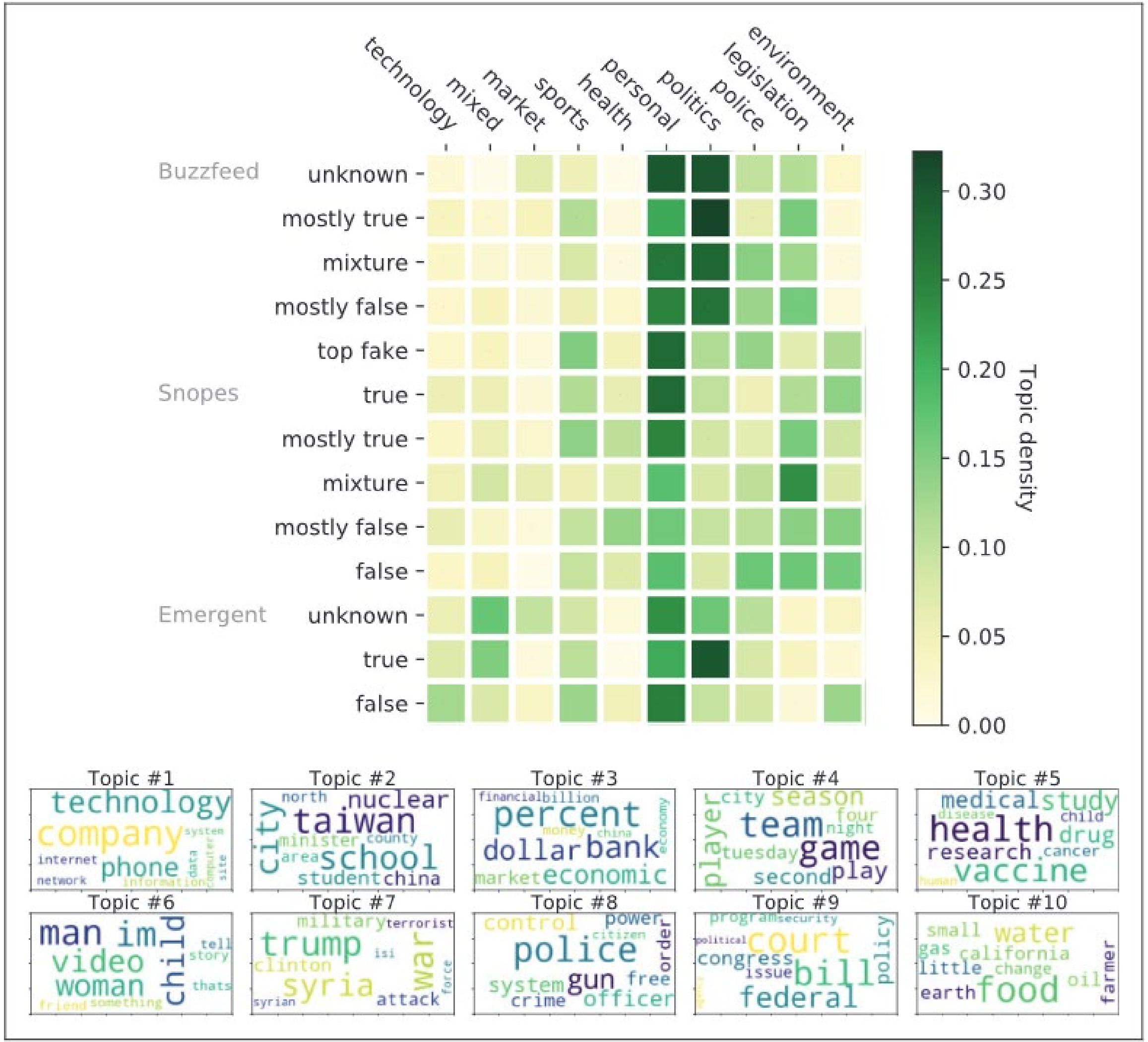
Corpus

Source	False	True	Small balanced sample	Large mixed sample
Snopes Silver	1,585	259	2 * 259	2 * 1,300
Buzzfeed USE	64	1,090	2 * 64	
Total	**1,649**	**1,349**	**646**	**2,600**

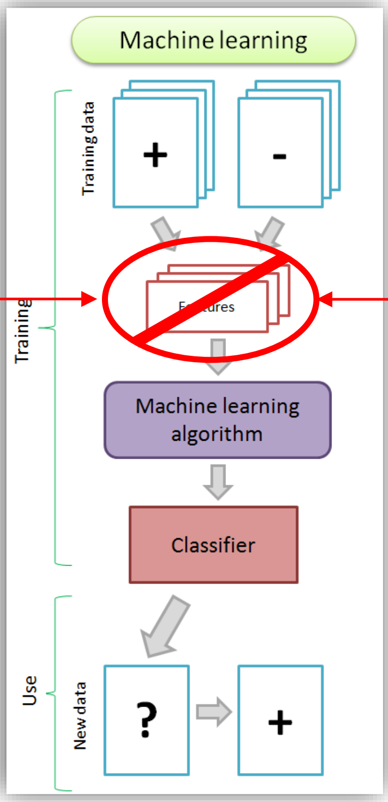
Snopes Silver, validado con crowdsourcing
Buzzfeed, noticias falsas de las elecciones en EE.UU
Cuando los juntamos, tenemos una mezcla de temas y personalidades

Usado como corpus de entrenamiento

Mezcla de temas y personalidades



¡Tenemos datos! 🥳



1. Aprendizaje supervisado
   SVMs con rasgos

2. Aprendizaje profundo
   LSTM
   CNN
   BERT

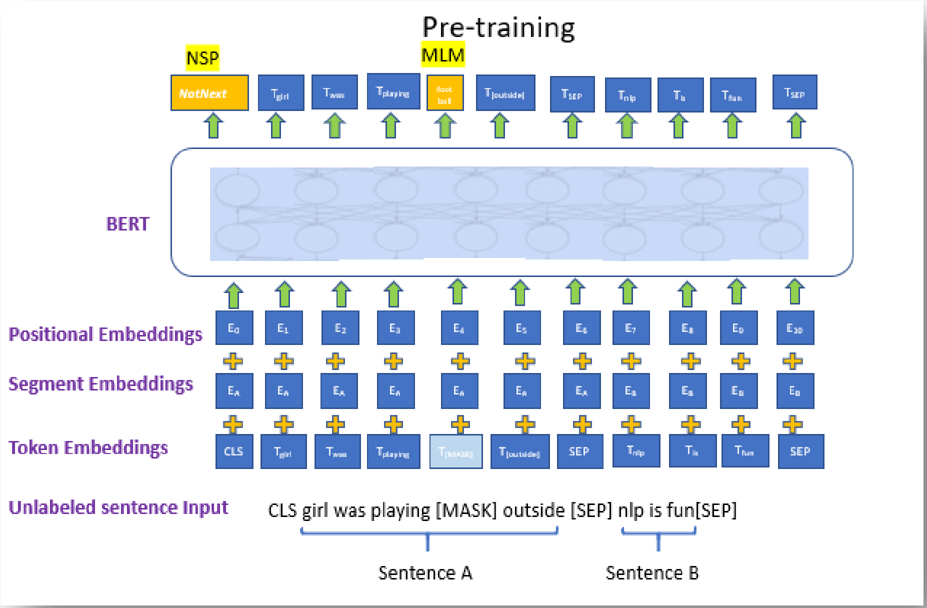
Falso o no

Métodos de clasificación – 1

- 1. SVMs – Máquinas de soporte vectorial
- Rasgos:
  - N-grams (TF-IDF)
  - Semánticos
    - LIWC, subjectividad
  - Sintácticos
    - POS – partes del discurso
    - Sustantivos, verbos, adjetivos, etc.
  - Nivel de lectura
    - Primaria/educación media/superior

Métodos de clasificación – 2

- 2. Aprendizaje profundo
- ULMFiT
  - Howard & Ruder 2018
  - Modelo de lenguaje pre-entrenado
  - Basado en vectores de palabras
- BERT
  - Modelo puntero de Google
  - También pre-entrenado



Corpus de entrenamiento y corpus de test

ENTRENAMIENTO	TEST

ENTRENAMIENTO

- Rashkin et al. (2017)
  - Propaganda/bulo/satírico/fiable
- Snopes Silver
  - Propio, mediante crowdsourcing
  - Corpus grande, temas mixtos
  - Corpus pequeño, menos mezcla

TEST

- Snopes Gold
  - Propio
  - Verificación del corpus de crowdsourcing
- Buzzfeed Top
  - Top 33 – noticias falsas
- Pérez Celebrity
  - Pérez-Rosas et al. (2017)
  - Noticias falsas sobre celebridades

Resultados

Table 4. Performance of different text classification models in various data scenarios measured by F1-score on training data as well as three test datasets

Data scenario	Model	Train	BuzzTop	SnopesGold	PerezCeleb
Rashkin mapped (8,000 train items)	SVM N-gram	98	94	54	56
	SVM N-gram+Sem	97	94	52	56
	SVM N-gram+Sem+Syn	96	91	53	59
	SVM All features	94	88	55	56
Big mixed (2,600 train items)	SVM N-gram	86	**97**	54	51
	SVM N-gram+Sem	86	**97**	54	51
	SVM N-gram+Sem+Syn	86	**97**	54	51
	SVM All features	83	85	50	52
	ULMFiT	83	95	51	50
Small balanced (646 train items)	SVM N-gram	96	88	67	64
	SVM N-gram+Sem	95	88	**70**	64
	SVM N-gram+Sem+Syn	86	88	**70**	**65**
	SVM All features	94	**97**	59	58
	ULMFiT	75	73	61	58

- Sesgo
  - Artículos sobre el mismo tema
  - La distribución por tema es importante
  - Detectar todo como bulo
- Los SMVs hacen un trabajo adecuado
- Los métodos de aprendizaje profundo necesitan muchos más datos

Rasgos – ¿cuáles son significativos?

- Semánticos
  - Palabras negativas
  - Adverbios
  - Utilidad del análisis de la opinion
    (Alonso, Vilares, Gómez-Rodríguez y Vilares 2021)
- LIWC
  - Contenido sexual
  - Pronombres
  - Adverbios
- Syntácticos
  - Verbos
  - Partículas
  - Adverbios
  - Pronombres (*they*=fake; *I*=true)
- Rasgos del texto
  - Bulos = más cortos
  - Menos apóstrofes
    - *do not* frente a *don't*

Método: Ratio y valor p en un análisis de correlación

Alonso, M. A., Vilares, D., Gómez-Rodríguez, C., & Vilares, J. (2021). Sentiment Analysis for Fake News Detection. *Electronics*, *10*(11), 1348.

Rasgos lingüísticos de los bulos

1 PREGUNTAS RETÓRICAS

- ¿Quién va a pagar por esto?
- Muchos españoles se preguntan, ¿qué pasa con la immigración?

2 PALABRAS NEGATIVAS

- una situación escalofriante
- severamente perturbador
- una burla de la gente decente

3 EXAGERACIONES

- Muchos adverbios y adjetivos
- alucinante testimonio de un ciudadano que asiste estupefacto al diálogo entre un trabajador de La Caixa y un immigrante

4 LENGUAJE DE OTREDAD/ IDENTIDAD

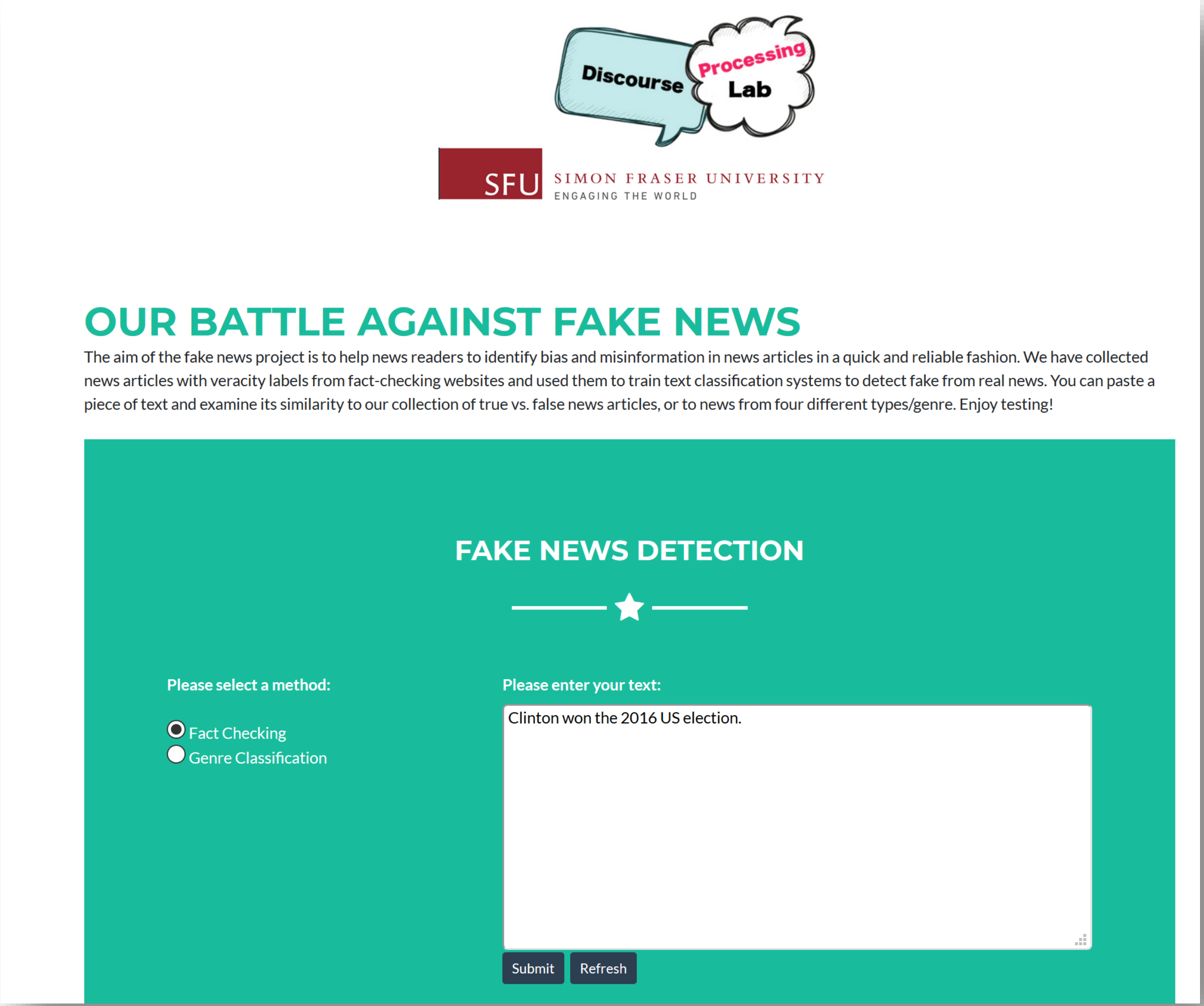
- Nosotros frente a ‘ellos’
- esa gente
- estos

5 MEZCLA DE ESTILO

- Mezcla de lenguaje formal e informal

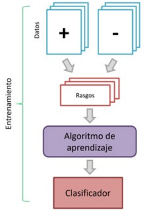
6 LENGUAJE NO ESTÁNDAR

- Errores gramaticales, faltas de ortografía
- El caso de los adolescentes de Macedonia



http://fakenews.research.sfu.ca/

En resumen



VARIAS PIEZAS DEL PUZLE

- Educación
- Propagación
- Verificación
- Tecnología

- Un problema social
- La tecnología y la IA como soluciones a problemas sociales

LA APORTACIÓN DEL PLN

- Necesitamos datos de calidad, anotados por expertas
  - Nueva Ley de Servicios Digitales
  - Exige a las plataformas compartir datos
- El aprendizaje profundo no siempre funciona
- En situaciones de ‘small data’, métodos clásicos
  - Con rasgos lingüísticos

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