

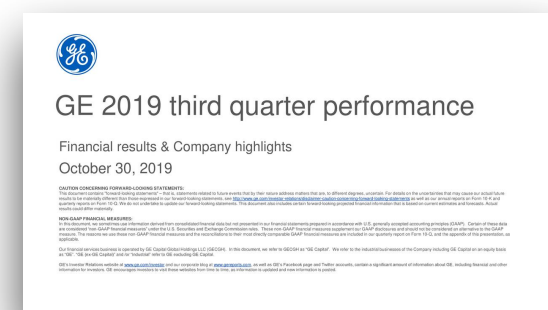
Automated Event Extraction for News-Based Counterdata

Katie Keith

Williams Statistics Colloquium

October 19, 2022

Age of abundant digitized texts



Text data for social sciences questions



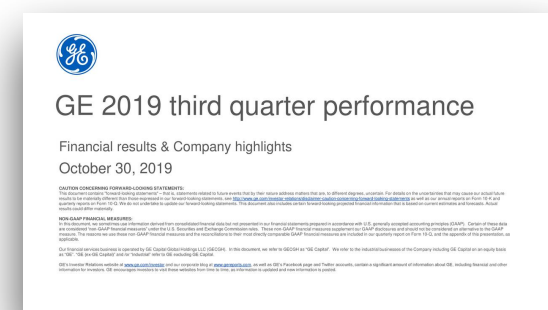
What drives newspapers' political slant?

Gentzkow and Shapiro, Econometrica, 2010



What is the nature of online censorship in China?

King et al., American Political Science Review, 2013



Manual analysis is costly at scale

What drives newspapers' political slant?

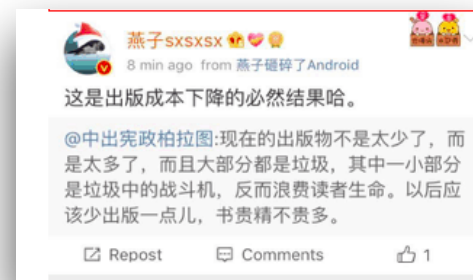
Gentzkow and Shapiro, Econometrica, 2010



All articles for 400 news outlets

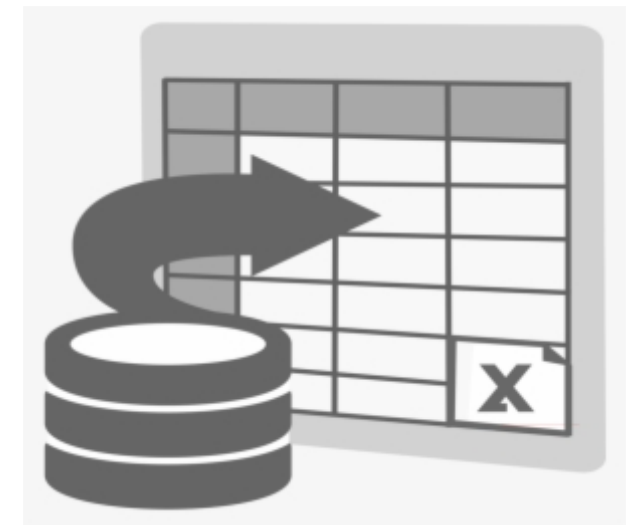
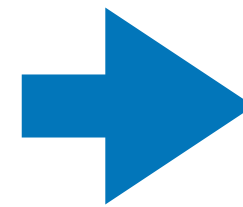
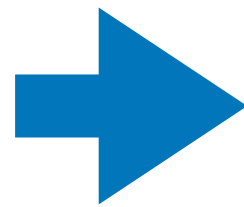
What is the nature of online censorship in China?

King et al., American Political Science Review, 2013



11 million posts

Natural language processing (NLP)



Focus of today's talk

Corpus-Level Evaluation for Event QA: The IndiaPoliceEvents Corpus Covering the 2002 Gujarat Violence

Andrew Halterman*
Massachusetts Institute of Technology
ahalt@mit.edu

Katherine A. Keith*
University of Massachusetts Amherst
kkeith@cs.umass.edu

Sheikh Muhammad Sarwar*
University of Massachusetts Amherst
smsarwar@cs.umass.edu

Brendan O'Connor
University of Massachusetts Amherst
brenocon@cs.umass.edu

Abstract

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1 Introduction

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Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 4240–4253
August 1–6, 2021. ©2021 Association for Computational Linguistics

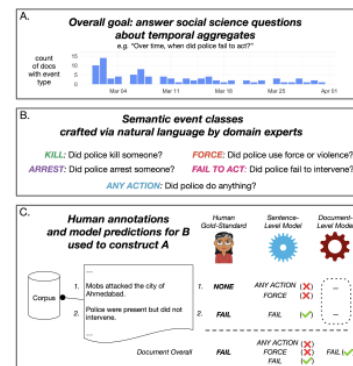


Figure 1: Motivation (A-B) and procedures (B-C) for this paper: A. Social scientists often use text data to answer substantive questions about temporal aggregates. B. To answer these questions, domain experts use natural language to define semantic event classes of interest. C. Our INDIAPOLICEEVENTS dataset: Humans annotate every sentence in the corpus in order to evaluate whether a system achieves full recall of relevant events. In production, computational models run B's queries to classify or rank sentences or documents, which are aggregated to answer A.

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Andy Halterman
Political Science



Katie Keith
Computer Science



Sheikh Sarwar
Computer Science



Brendan O'Connor
Computer Science

Political science-motivated research questions



Andy Halterman
Political Science

1.

Q: Does variation in party control of state government affect whether police failed to intervene in communal violence?

2.

Challenges

- No official records. Only news articles.
- Reading documents manually is costly.

3.

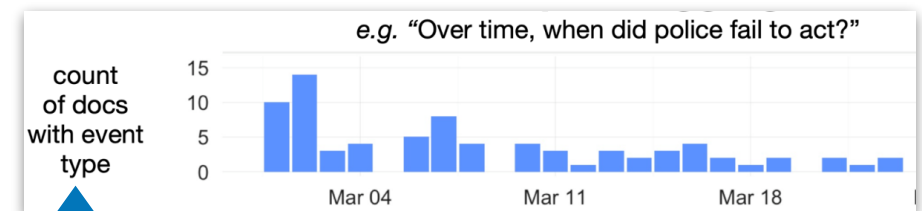
Use NLP to automate extracting events



Violence in Gujarat, India 2002

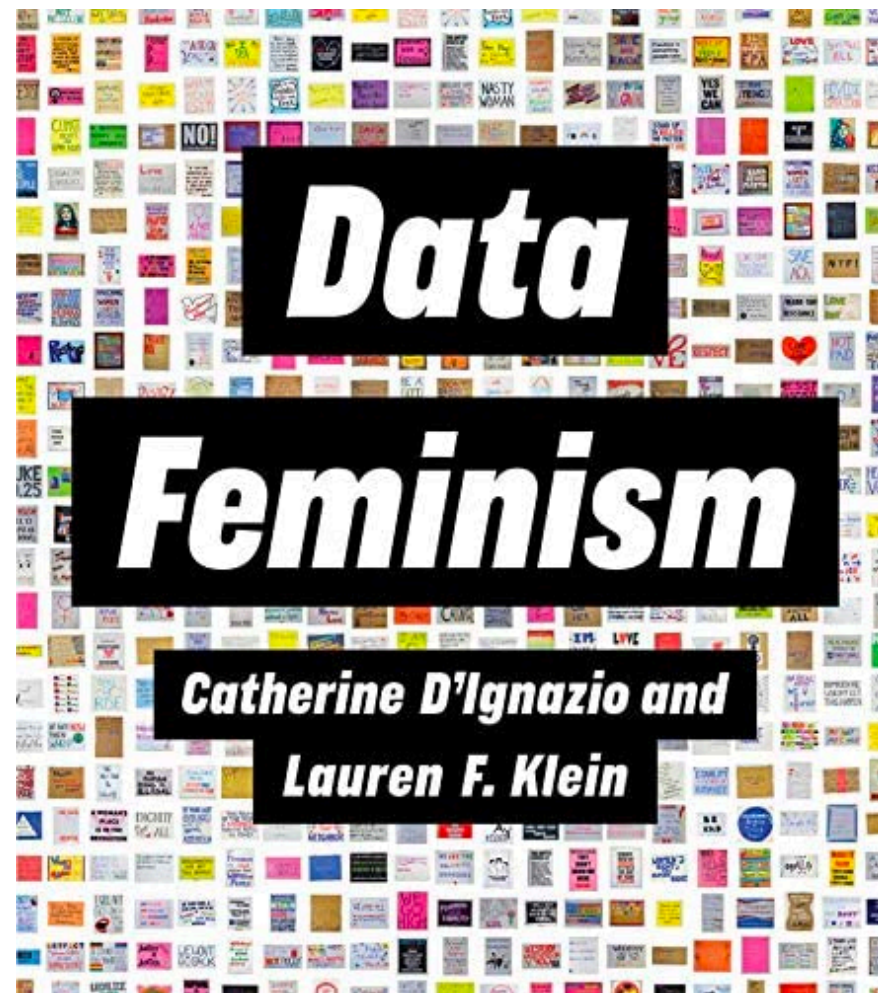


Train fire kills Hindu Pilgrims, Feb. 27, 2002
Photo Credit: New York Times



Media bias outside the scope of this talk

Counterdata is the grassroots collection
of missing datasets



Events

Who did what to whom?

Police killed [PERSON].

Even simple event types present challenges

Police killed PERSON.

Police officers spotted the butt of a handgun in **Alton Sterling**'s front pocket and saw him reach for the weapon before **opening fire**, according to a Baton Rouge Police Department search warrant filed Monday that offers the first police account of the events leading up to **his fatal shooting**.

Keith et al. Identifying civilians killed by police with distantly supervised entity-event extraction. EMNLP, 2017.

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Police killed PERSON.

long-range dependencies

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coreference

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coreference

*event
coreference*

Events

Who did what to whom?

Hovy et al. *Events are Not Simple: Identity, Non-Identity, and Quasi-Identity*. Workshop on EVENTS, 2013.

Abend and Rappoport. *The State of the Art in Semantic Representation*. ACL, 2017.

Automated event extraction has a large academic literature...

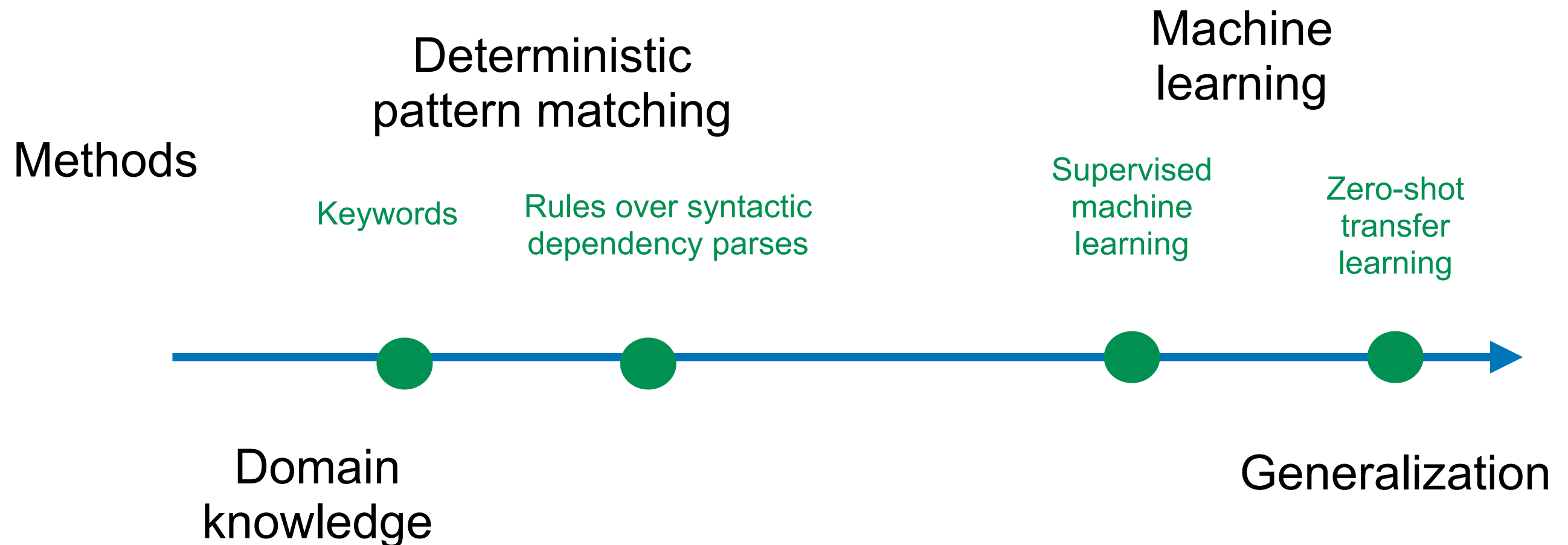
in the social sciences

Schrodt et al., 1994; King and Lowe, 2003; Hanna, 2014; Hammond and Weidmann, 2014; Boschee et al., 2015; Beieler et al., 2016; Osorio and Reyes, 2017

in computer science

Grishman, 1997; McCallum, 2005; Aguilar et al., 2014; Hovy et al., 2013; Levy et al., 2017; Abend and Rappoport, 2017; Grishman, 2019; Liu et al., 2020; Du and Cardie, 2020

Approaches to Automated Event Extraction



Mitchell. The Need for Biases in Learning Generalizations. 1980.

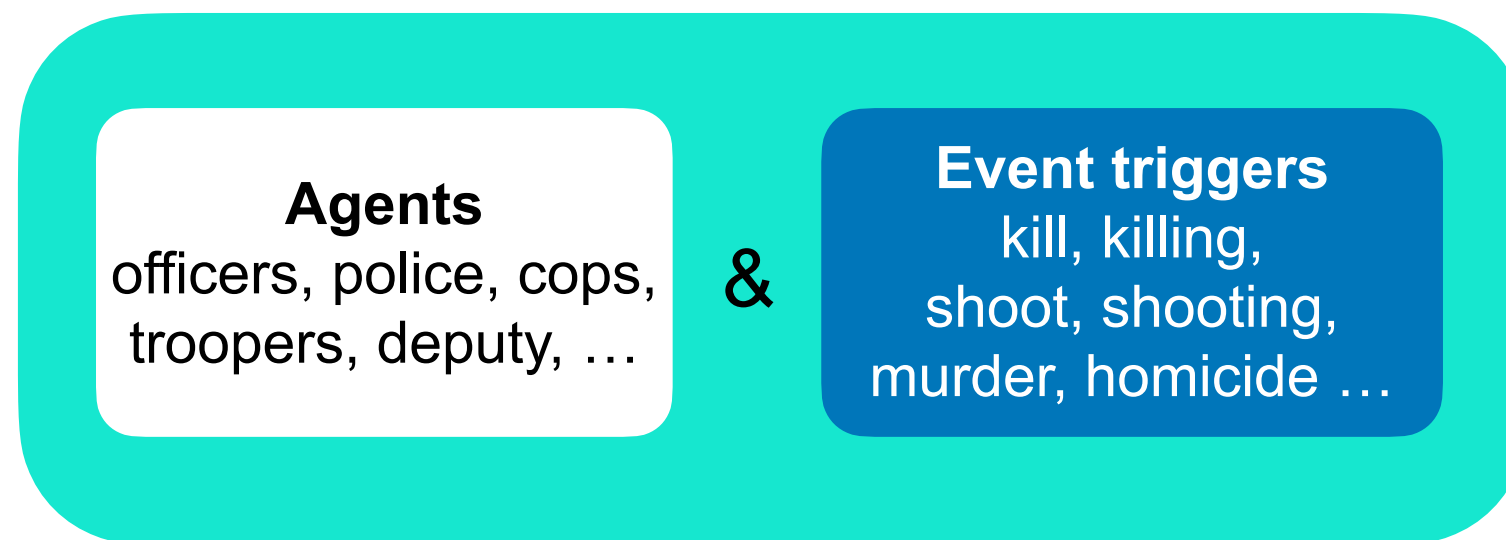
Deterministic Keyword Matching

Input: sentences

*PERSON was **fatally shot** by **police**.*

***Officers** reported PERSON was **killed** in a car accident.*

Method:
Keyword matching



Output: Classification

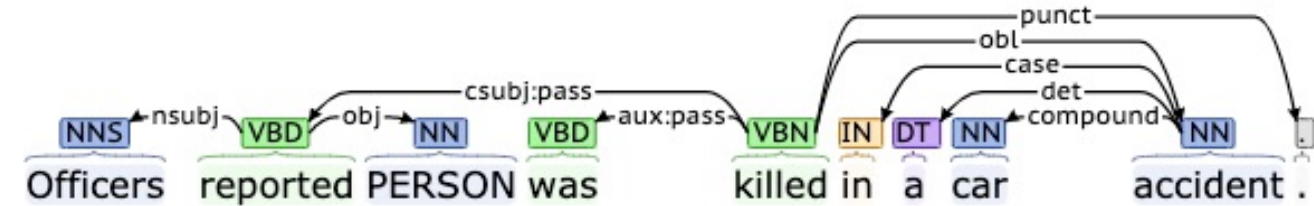
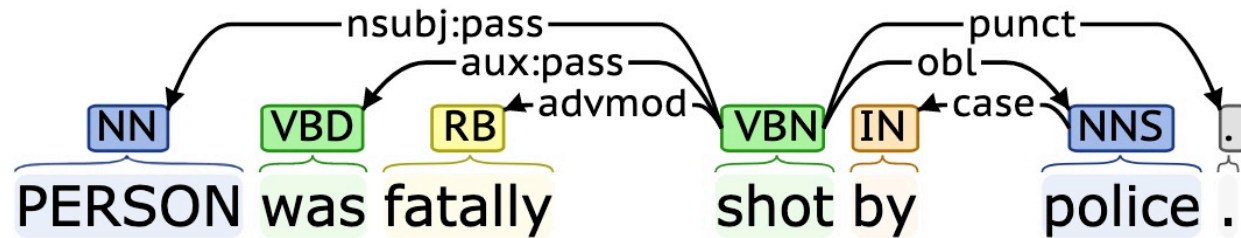
Yes

~~Yes~~

Issue: many
false positives
(low precision)

Deterministic Syntax Matching

Input: automatically infer dependency parse trees over sentences



Method: Rules over dependency paths

PERSON <-nsubj:pass <-

kill, killing,
shoot, shooting,
murder, homicide ...

->obl ->

officers, police,
cops, troopers,
deputy, ...

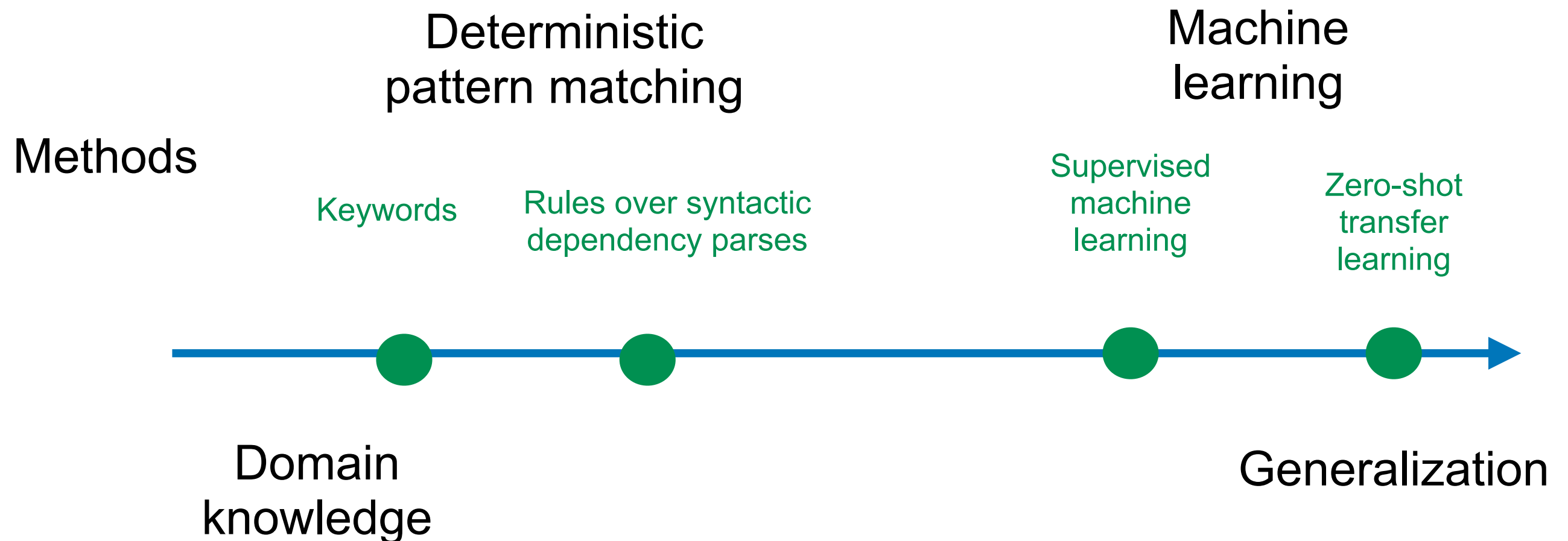
Output: Classification

Yes

~~No~~

Issue: Difficult for a domain expert to list all possible rules (*low recall*)

Approaches to Automated Event Extraction



Mitchell. The Need for Biases in Learning Generalizations. 1980.

Supervised Machine Learning

1. **Gather** training data

Police killed PERSON.



Yes/No

2. **Humans label** training data

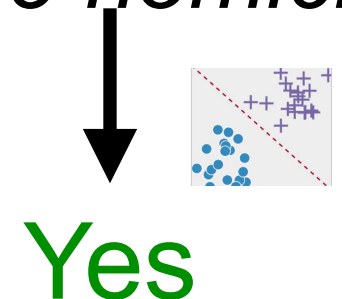
Issue: Costly

3. **Train model:** statistical pattern matching between inputs and labels

- Our 2017 work:
- *logistic regression* with bag of words features
 - *convolutional neural networks* initialized with pre-trained word embeddings

4. **Inference:** (generalization) apply trained model on unseen inputs

PERSON died in a police homicide.




Yes

AI Hype

The New York Times

A Learning Advance in Artificial Intelligence Rivals Human Abilities

Give this article



Human or Machine?

Humans and machines were given an image of a novel character (represented atop each grid) and then asked to copy it. Brenden Lake

By John Markoff
Dec. 10, 2015

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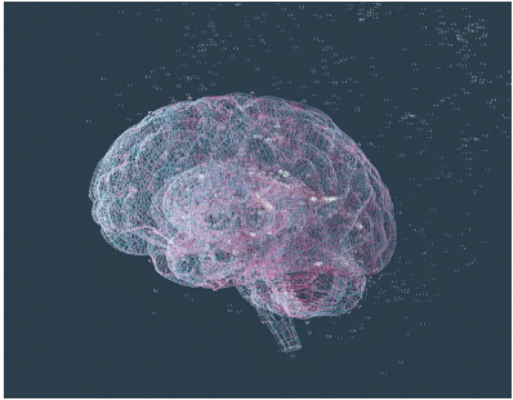
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Google Engineer Claims AI Chatbot Is Sentient: Why That Matters

Is it possible for an artificial intelligence to be sentient?

By Leonardo De Cosmo on July 12, 2022



Credit: Boris SV/Getty Images

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Gary Marcus

Pre-training with large-scale language models

Huge performance gains in recent years with **large-scale language models** trained on scrapes of the web

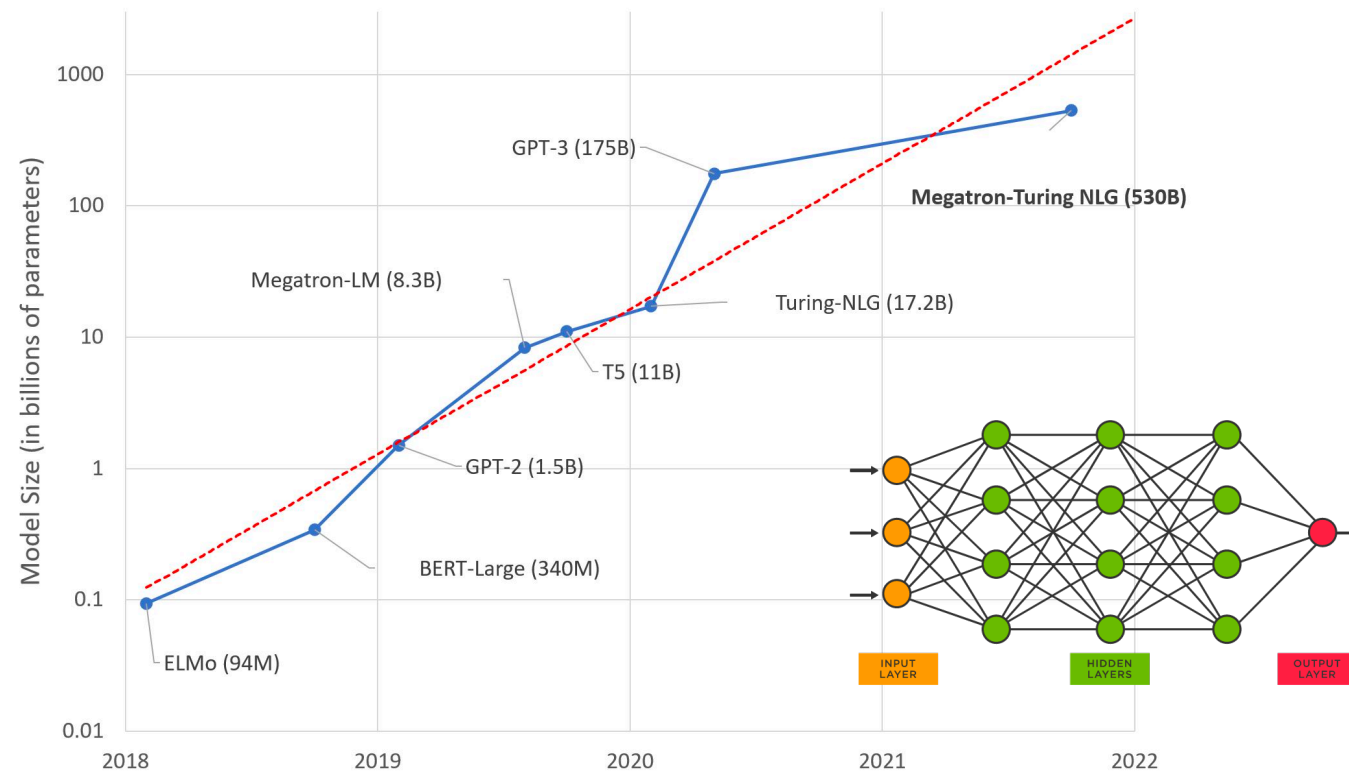


Figure credit: Hugging Face

Self-supervision: Masked language modeling (MLM) objective function

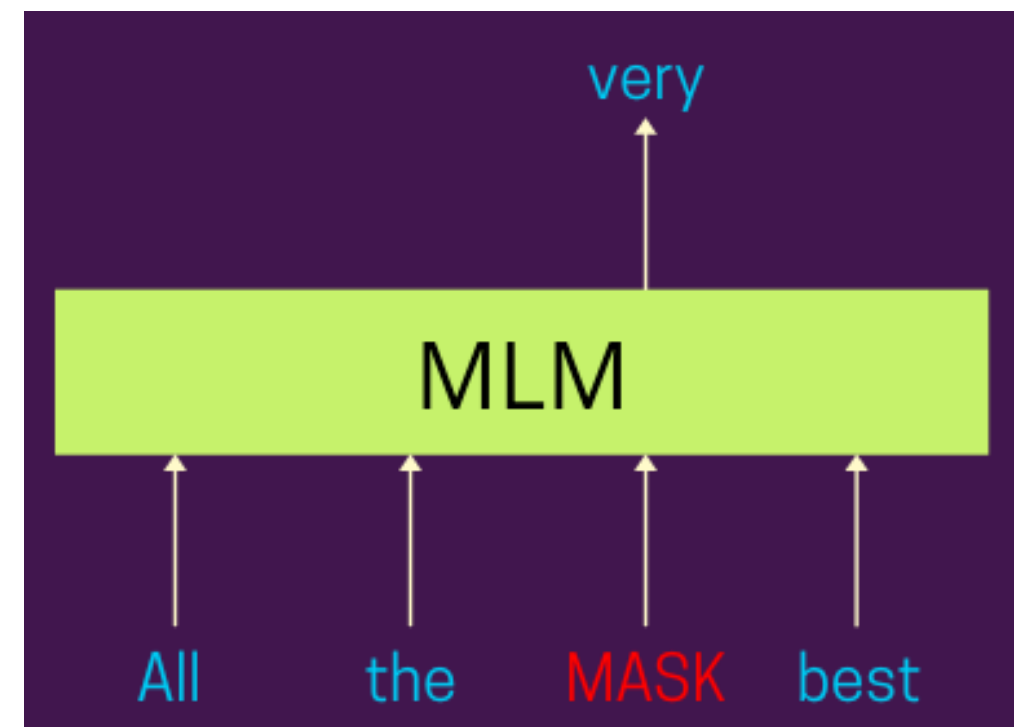


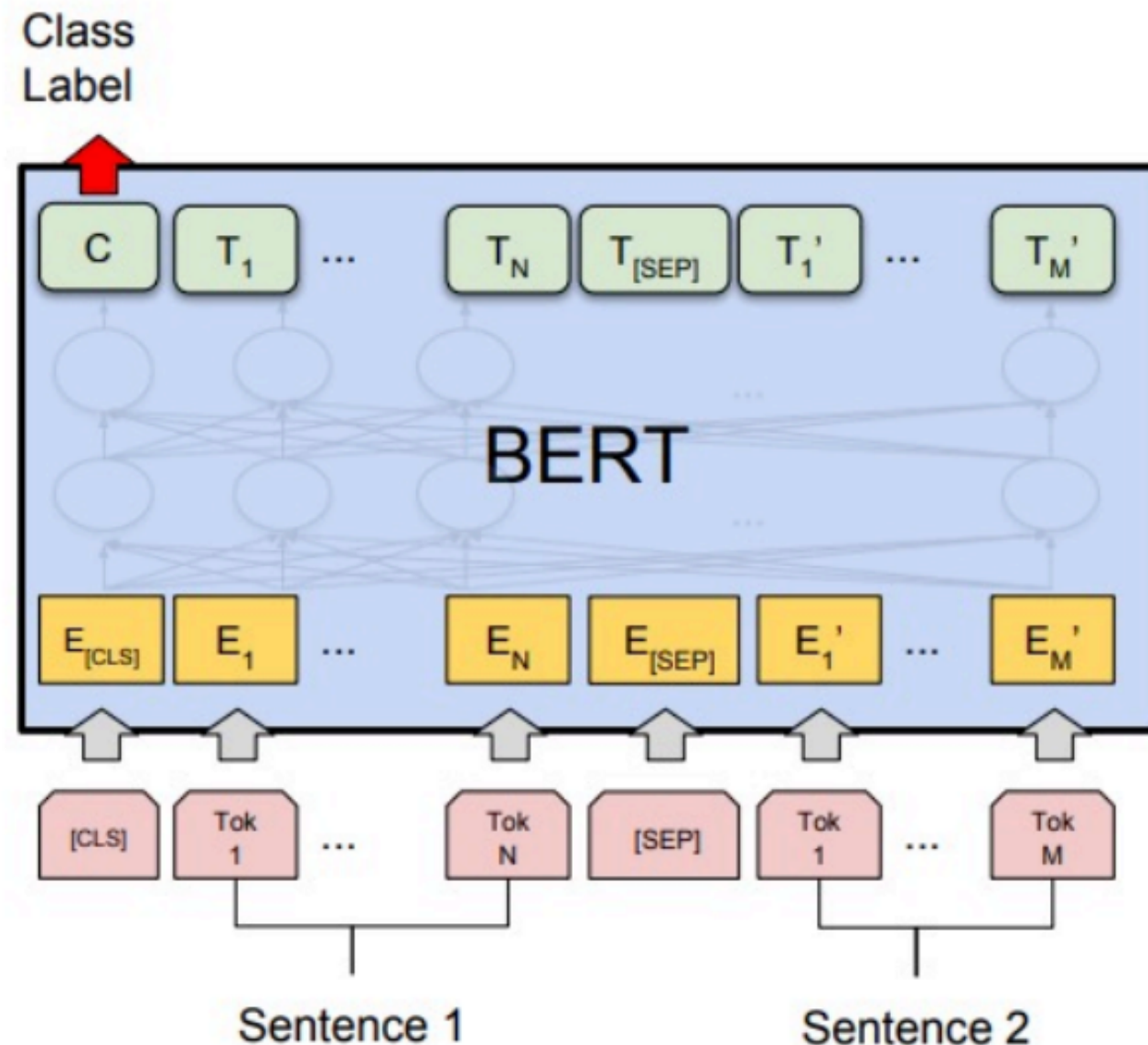
Figure credit: Prakhar Mishra, [blog](#)

Zero-Shot Transfer Learning

1. **Pre-train** large-scale language model
2. **Fine-tune** on a task with labeled data
3. Apply trained model **zero-shot** to our dataset

2. Fine-tuning on a task with labeled data

Entailment
Neutral
Contradiction



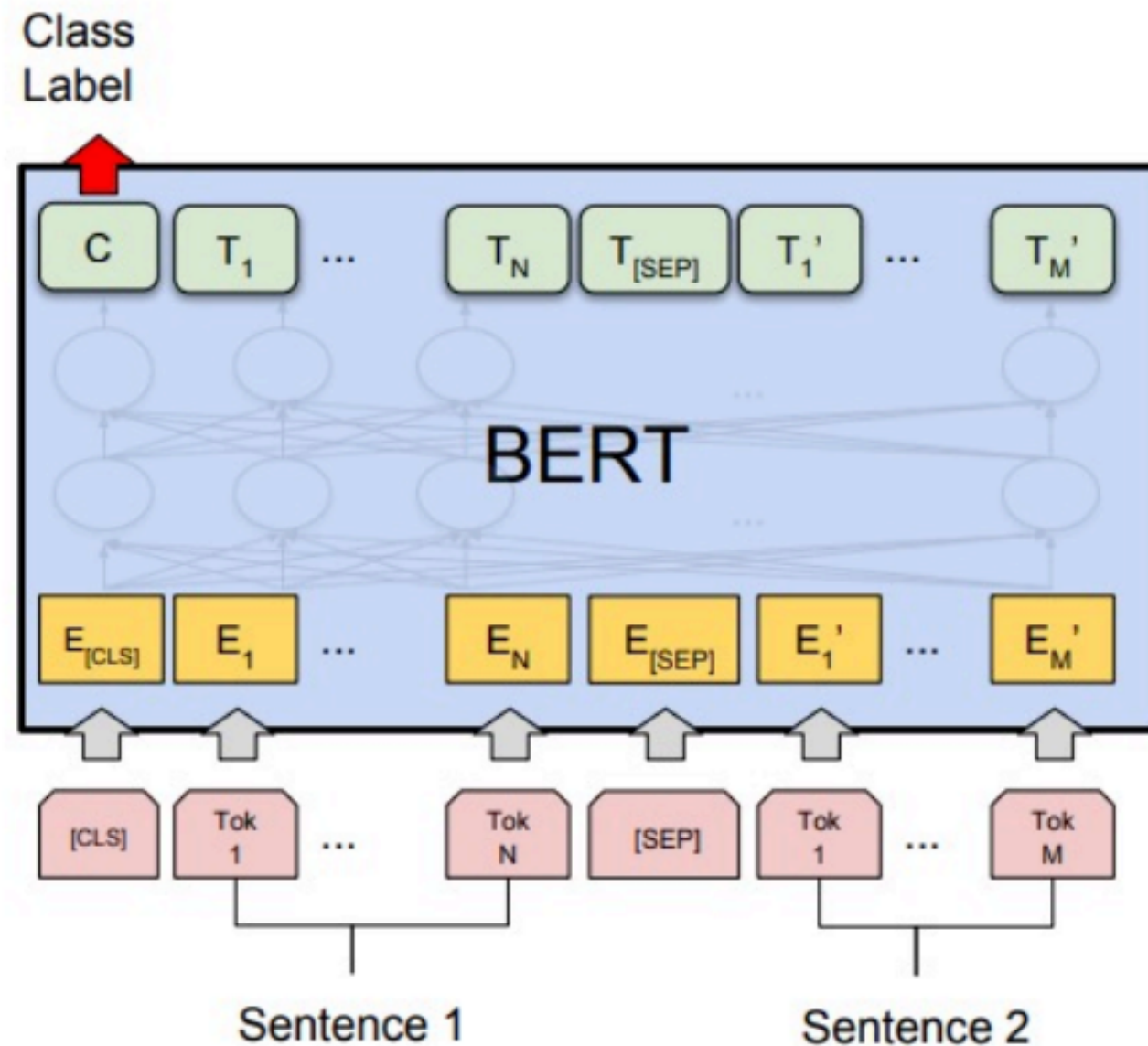
A soccer game with
multiple males playing.

Some men are playing
a sport.

Bowman et al. ACL, 2015

3. Apply trained model **zero-shot** to our dataset

Entailment
Neutral
Contradiction



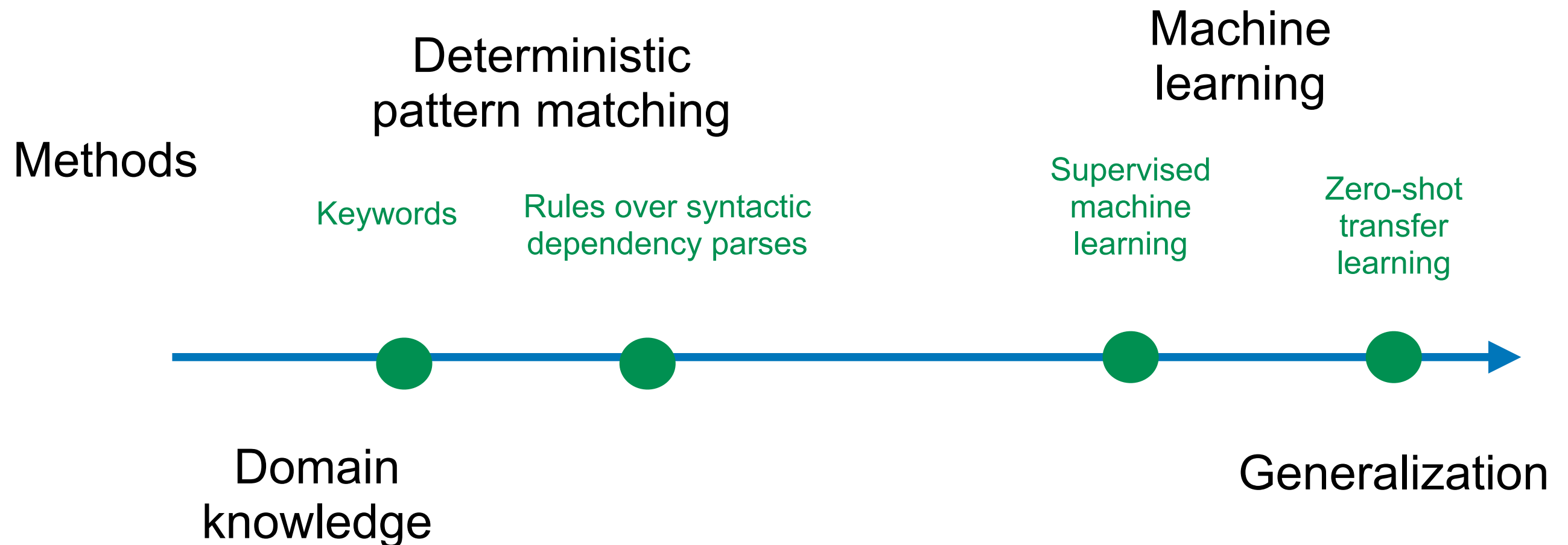
Prompt

Police killed
someone.

Sentence from
our dataset

Yesterday, 97 died in
police firing.

Approaches to Automated Event Extraction



Mitchell. The Need for Biases in Learning Generalizations. 1980.

What was our original problem again?

International-relations motivated research questions



Andy Halterman
Political Science

1.

Q: Does variation in party control of state government affect whether police failed to intervene in communal violence?

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Challenges

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Use NLP to automate extracting events



Violence in Gujarat, India 2002



Train fire kills Hindu Pilgrims, Feb. 27, 2002
Photo Credit: New York Times



Novel dataset created for empirical evaluation



- *Times of India*
- Filter to March 2002 and “Ayodha” OR “Gujarat”
- **Results in 1,257 articles, 21,391 sentences**
- Every sentence annotated with 2 annotators + adjudication round

Annotation interface

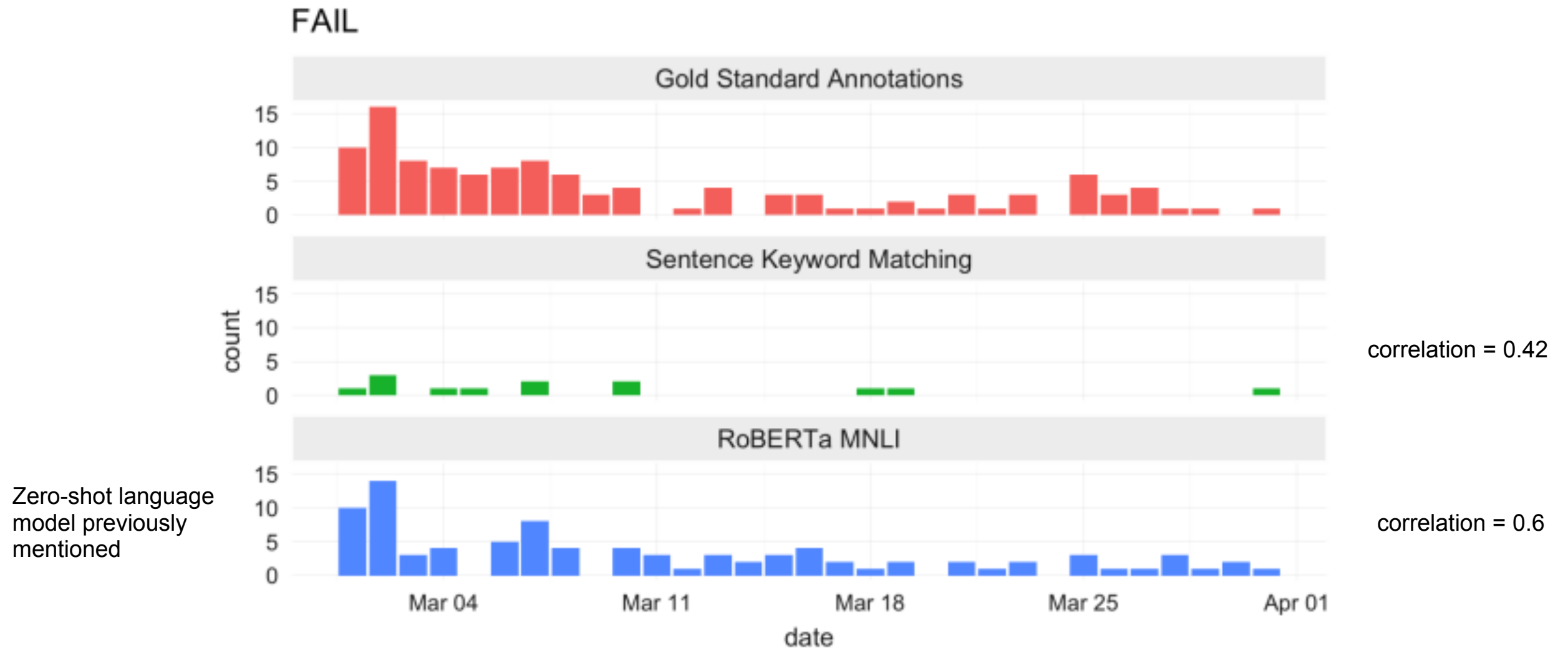
On Sunday, a mob gathered carrying swords, hockey sticks and other weapons. In response, the police rushed to the spot to quell the violence and arrested ten people. **Two people died due to police firing and another three were injured from the shooting.** An officer was detained due to unethical conduct.

<input checked="" type="checkbox"/> Did police kill someone?	1
<input type="checkbox"/> Did police arrest someone?	2
<input type="checkbox"/> Did police fail to act or not intervene?	3
<input checked="" type="checkbox"/> Did police use other force or violence?	4
<input type="checkbox"/> Did police say or do something else (not included above)?	5

Dataset publicly available

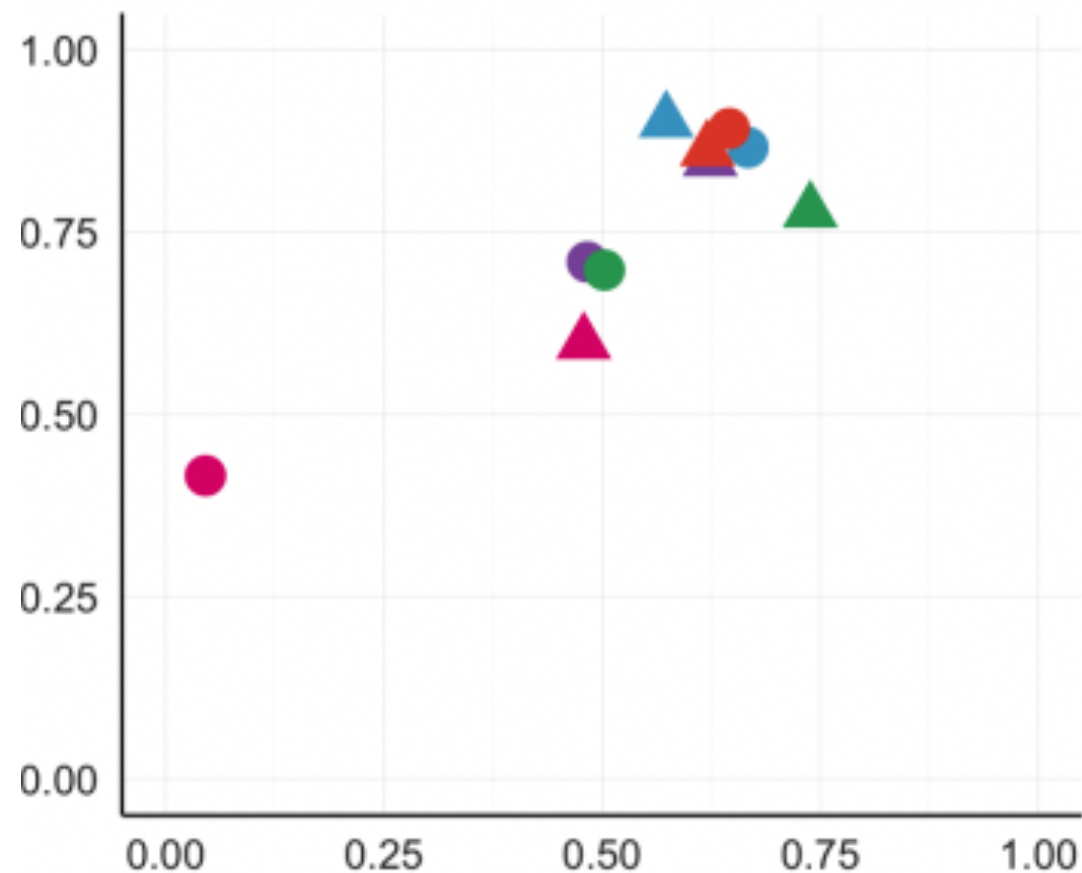
<https://github.com/slanglab/IndiaPoliceEvents>

Evaluation highlights



Evaluation highlights

Temporal aggregates:
correlation between
human gold-standard and model



Event Class

- KILL
- ARREST
- FAIL
- FORCE
- ANY ACTION

Model

- Keyword-Sent
- RoBERTA+MNLI

Zero-shot language
model previously
mentioned

Manual error analysis



Model assigns high positive probability to sentences that should be classified as **negatives**

“ [...] scores of people have been killed in rural Gujarat due to police failure...”

“Police said that two persons had been killed [...]”

Please read our paper for more details!

Corpus-Level Evaluation for Event QA: The IndiaPoliceEvents Corpus Covering the 2002 Gujarat Violence

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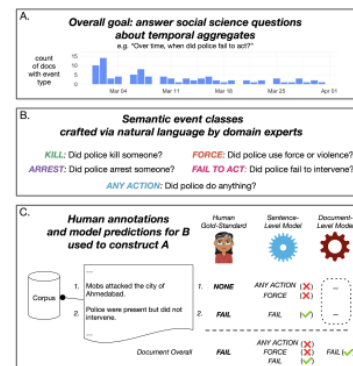


Figure 1: Motivation (A-B) and procedures (B-C) for this paper: A. Social scientists often use text data to answer substantive questions about temporal aggregates. B. To answer these questions, domain experts use natural language to define semantic event classes of interest. C. Our INDIAPOLICEEVENTS dataset: Humans annotate every sentence in the corpus in order to evaluate whether a system achieves full recall of relevant events. In production, computational models run B's queries to classify or rank sentences or documents, which are aggregated to answer A.

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Andy Halterman
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Sheikh Sarwar
Computer Science



Brendan O'Connor
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CSCI 375

Natural Language Processing

Spring 2023



CATALOG SEARCH

Natural language processing (NLP) is a set of methods for making human language accessible to computers. NLP underlies many technologies we use on a daily basis including automatic machine translation, search engines, email spam detection, and automated personalized assistants. These methods draw from a combination of algorithms, linguistics and statistics. This course will provide a foundation in building NLP models to classify, generate, and learn from text data.

The Class:

Format: lecture
Limit: 24
Expected: 24
Class#: 3296
Grading: no pass/fail option, no fifth course option

Requirements/Evaluation:

Evaluation based on assignments, projects, and exams.

Prerequisites:

CSCI 136, and either CSCI 256 or STAT 201/202.

Enrollment Preferences:

current or expected Computer Science majors.

Distributions:



Division III
Quantitative/Formal Reasoning

QFR Notes:

The course will consist of programming assignments and problem sets in which quantitative/formal reasoning skills are practiced and evaluated.

View Book Information

Updated 9:31 AM

CLASSES	DREQ	INSTRUCTORS	TIMES	CLASS#	ENROLL	CONSENT
CSCI 375 - 01 [S] LEC Natural Language Processing		Katie A. Keith	MWF 10:00 am - 10:50 am	3296	Open	None
CSCI 375 - 02 [S] LEC Natural Language Processing		Katie A. Keith	MWF 11:00 am - 11:50 am	3297	Open	None



Diaries of Social Data Research

Diaries of Social Data Research

By Katherine A. Keith & Lucy Li


Large-scale data has become a major component of research about human behavior and society. But how are interdisciplinary collaborations that use large-scale social data formed and maintained? What obstacles are encountered on the journey from idea conception to publication? In this podcast, we investigate these questions by probing the "research diaries" of scholars in computational social science and adjacent fields. We unmask the research process with the hope of normalizing the challenges of and increasing

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