Reliable characterizations of NLP systems as a social responsibility

Christopher Potts

Stanford Linguistics and the Stanford NLP Group

ACL-IJCNLP 2021

More impact than ever before

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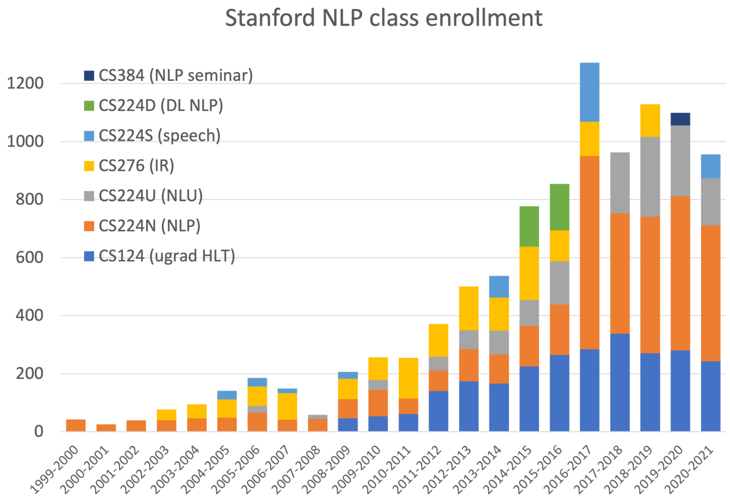
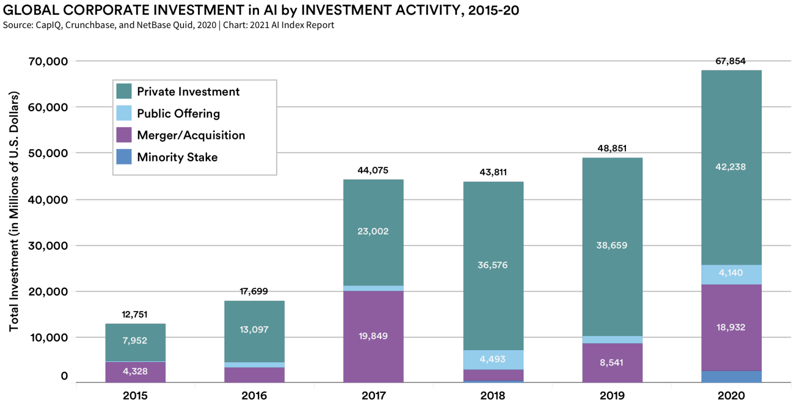


More impact than ever before

Stanford occupies the academic forefront of a global explosion in interest around AI. Fei-Fei Li, who created the ImageNet dataset in 2009 — a key milestone in the AI subdiscipline of computer vision — joined Stanford's CS faculty in 2009. In 2010, Stanford's Chris Manning developed CoreNLP, a set of AI-powered natural language analysis tools, which is now used by over 900 companies. In addition to leading AI scholarship, there has been an expansion in AI curricula, with enrollment in AI classes quadrupling over the decade, attracting fewer than 2,000 students in 2010 to more than 8,000 students by 2020. The number of AI-related classes in the CS Department also tripled, increasing from 25 to 77 classes.

Stanford Tech History Project

More impact than ever before



2021 AI Index

More impact than ever before

- **Natural Language Processing (NLP) outruns its evaluation metrics:** Rapid progress in NLP has yielded AI systems with significantly improved language capabilities that have started to have a meaningful economic impact on the world. Google and Microsoft have both deployed the BERT language model into their search engines, while other large language models have been developed by companies ranging from Microsoft to OpenAI. Progress in NLP has been so swift that technical advances have started to outpace the benchmarks to test for them. This can be seen in the rapid emergence of systems that obtain human level performance on SuperGLUE, an NLP evaluation suite developed in response to earlier NLP progress overshooting the capabilities being assessed by GLUE.

2021 AI Index

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- Language preservation

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Donahue et al. 2020

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"Person, Shoes, Tree. Is the Person Naked?" What People with Vision Impairments Want in Image Descriptions

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RQ2: Participants shared that they want image descriptions that clarify the purpose of the image in the news sources. As P28 noted, *"So usually if there is an image attached to an article, there's a reason for that image. They may take 1500 pictures of a protest, but only choose two [to] be on the website. Why did those two pictures get chosen?"* In P16's words, *"I think it's [images are] just information to tell the story. But, just saying 'image' does nothing. If there's an image, tell me why it's important, I guess."*

RQ2: Participants shared that they want image descriptions in SNS that help them understand the purpose of the image. As P16 noted, *"People share a lot of personal images. You have to infer why they're sharing it based on their strange texts. More detail is necessary."* We learned that purpose is especially important when the person posting the image does not provide a comment or the comment did not directly reference the image content.

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TOP 9 TAKEAWAYS

1 **AI investment in drug design and discovery increased significantly:** "Drugs, Cancer, Molecular, Drug Discovery" received the greatest amount of private AI investment in 2020, with more than USD 13.8 billion, 4.5 times higher than 2019.

Global Edition Artificial Intelligence

Using natural language processing to unlock SDOH in unstructured EHR data

Social determinants of health can make a big difference in health outcomes. A physician expert in NLP highlights how the AI technology can unearth gold in EHRs.

By Bill Siwicki | February 19, 2021 | 01:26 PM

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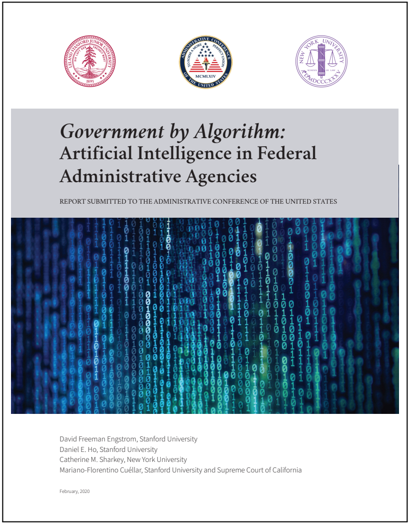
Government by Algorithm:
Artificial Intelligence in Federal Administrative Agencies

REPORT SUBMITTED TO THE ADMINISTRATIVE CONFERENCE OF THE UNITED STATES

David Freeman Engstrom, Stanford University
Daniel E. Ho, Stanford University
Catherine M. Sharkey, New York University
Mariano-Florentino Cuéllar, Stanford University and Supreme Court of California

February, 2020

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C. "Registrant" Misconduct: The Form ADV Fraud Predictor

A fourth and final tool, the Form ADV Fraud Predictor, helps SEC staff predict which financial services professionals may be violating federal securities laws.[32] The tool parses so-

[. . .]

Because Form ADVs are composed of free text, NLP algorithms are used to normalize the inputs in order to detect instances of fraud. Because it is difficult to observe fraud directly,[35] the SEC has developed a multi-step process to automate the fraud detection pipeline. After a pre-processing step that algorithmically converts PDF forms into useable blocks of text,[36] an unsupervised NLP technique (Latent Dirichlet allocation or LDA[37]) generates topics that best describe the words in each document.[38] This approach identifies topics in the documents without prior knowledge about what the topics will be.

The final step deploys a supervised learning algorithm to flag current registrants as "high," "medium," and "low" priority for further investigation by SEC staff.[39] The algorithm is trained on a dataset of past registrants that were referred to the agency's

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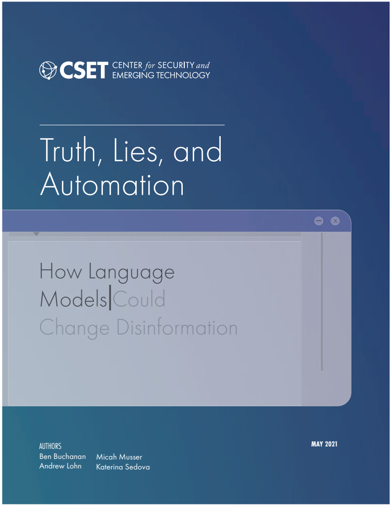

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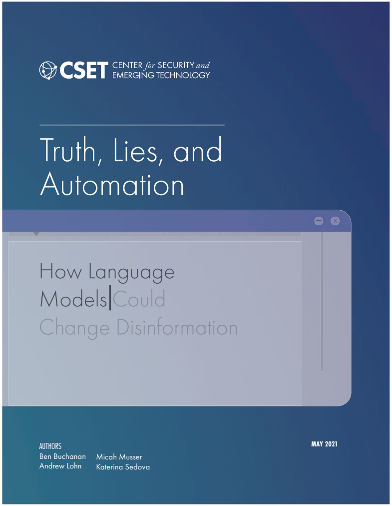

Clark et al. 2021

Notions of social responsibility

Edsall 1975, 1981

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4. Consequences

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Raises a *different* set of challenging questions.

Limited goals for today

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Approved and
disapproved uses

Limited goals for today

Pernicious
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Limited goals for today

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Approved and
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Safety in
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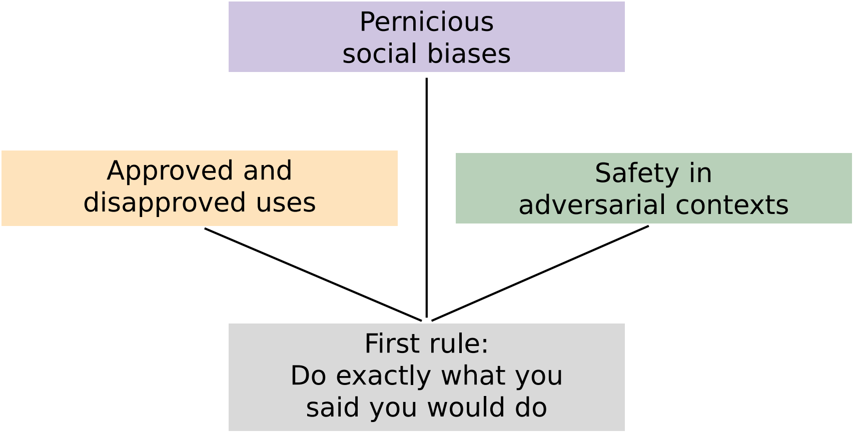
Limited goals for today



Roles to have in mind

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Schlangen 2020

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4. Leader : Can we automate our question answering?

Schlangen 2020

Overview

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1. Benchmark datasets: Delimit responsible use

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2. System assessment: Connect with real-world concerns

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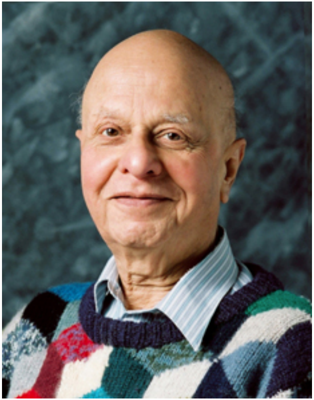
3. Discussion

Benchmark datasets

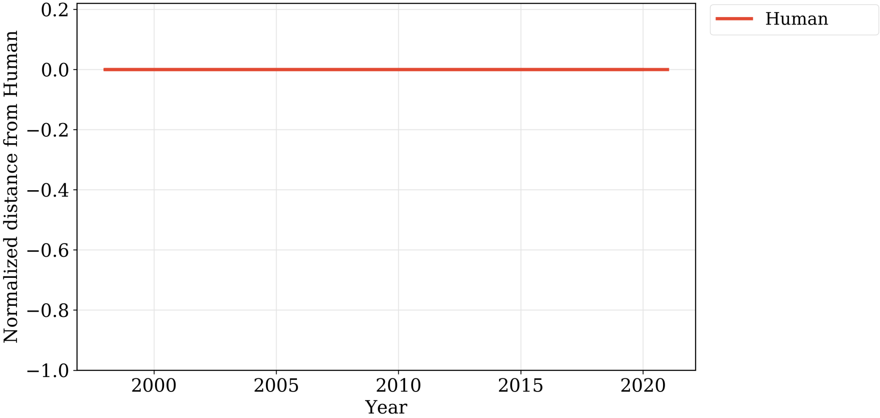
Seeing farther than ever before



Aravind Joshi: Datasets as the telescopes of our field

Photo credit: JoshiFest

Benchmarks saturate faster than ever



Kiela et al. 2021

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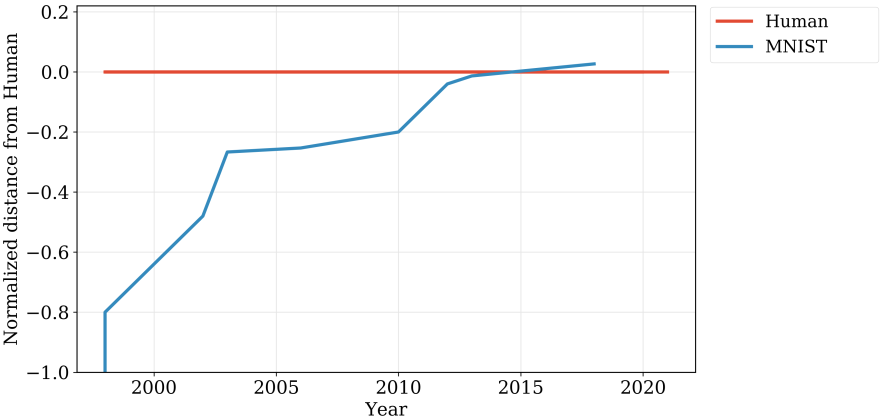

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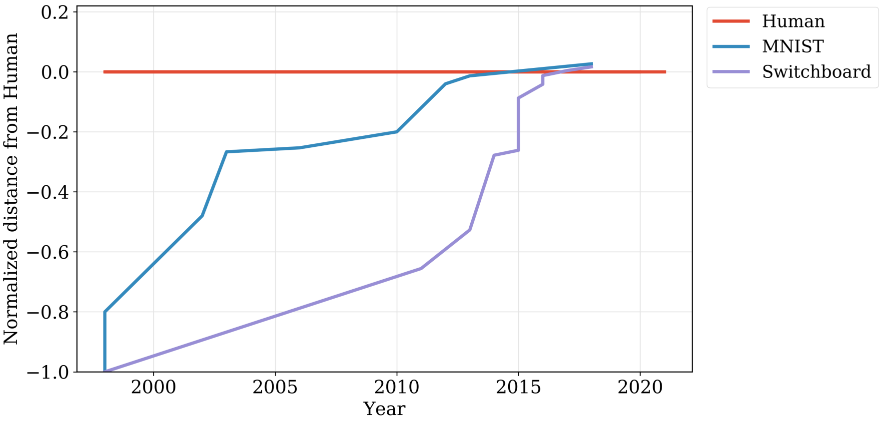

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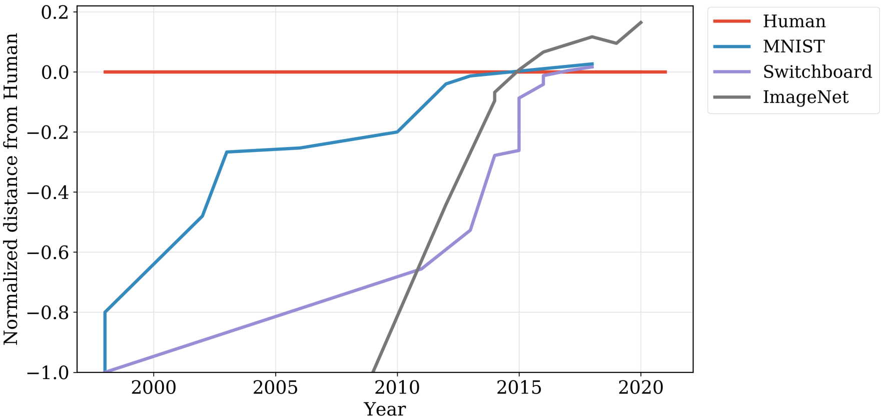

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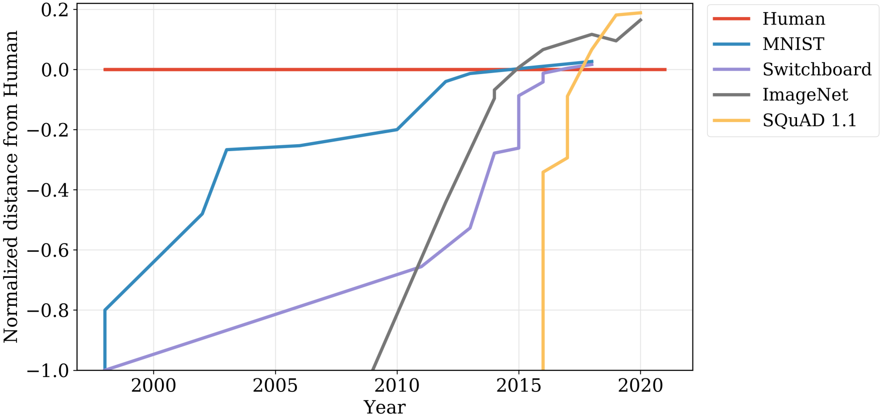

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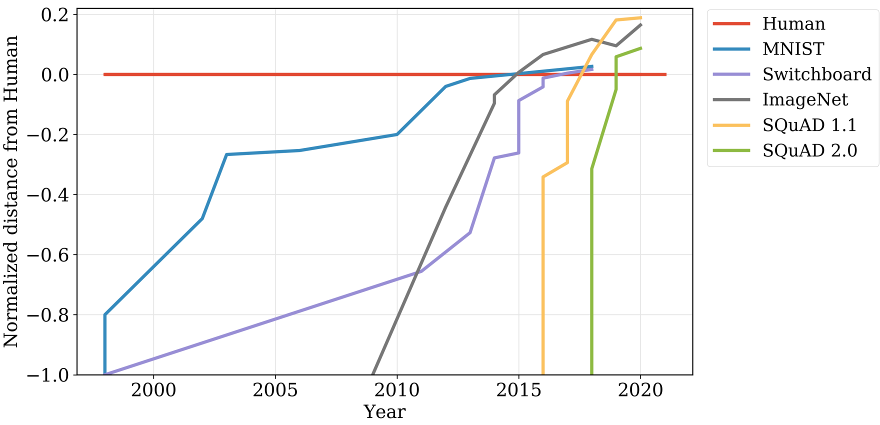

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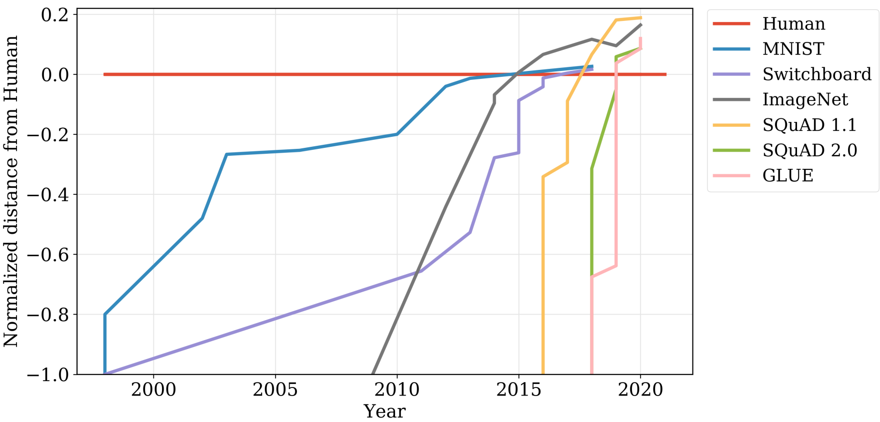

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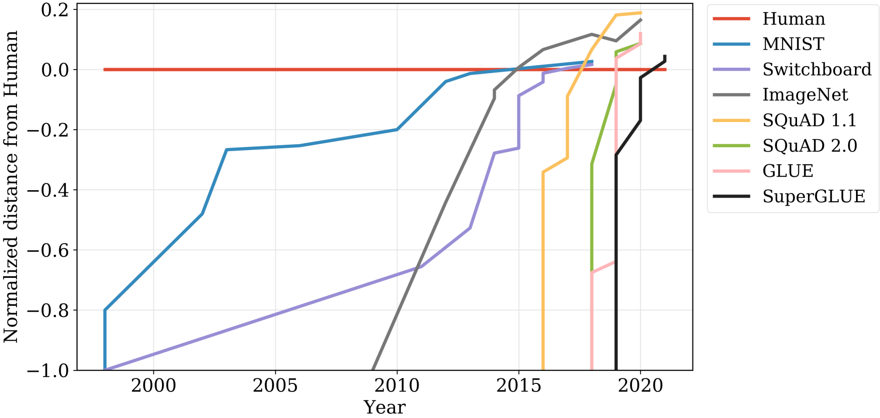

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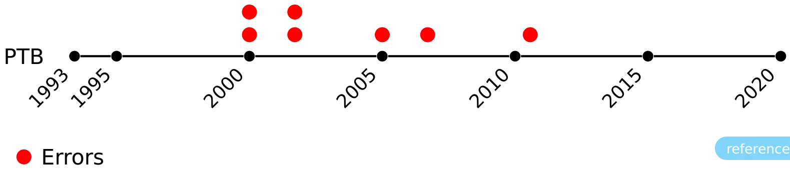
Limitations found more quickly



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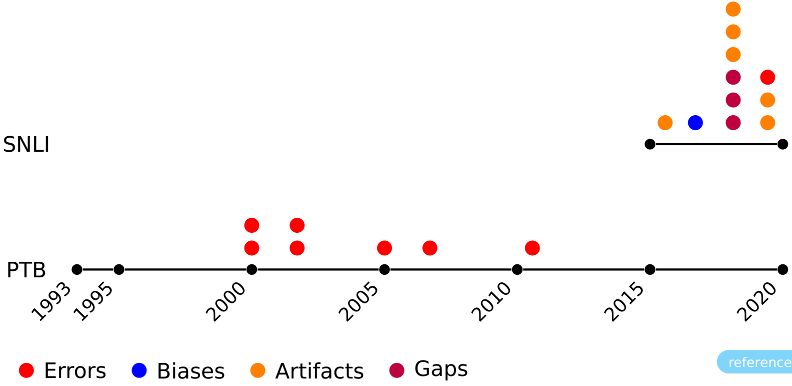

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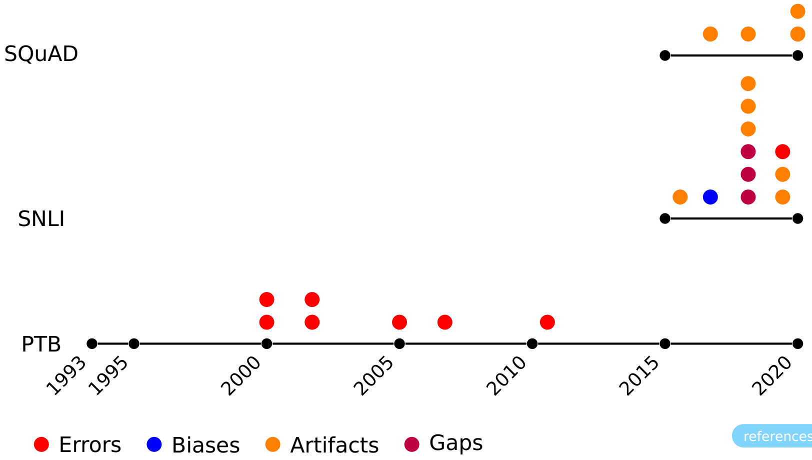

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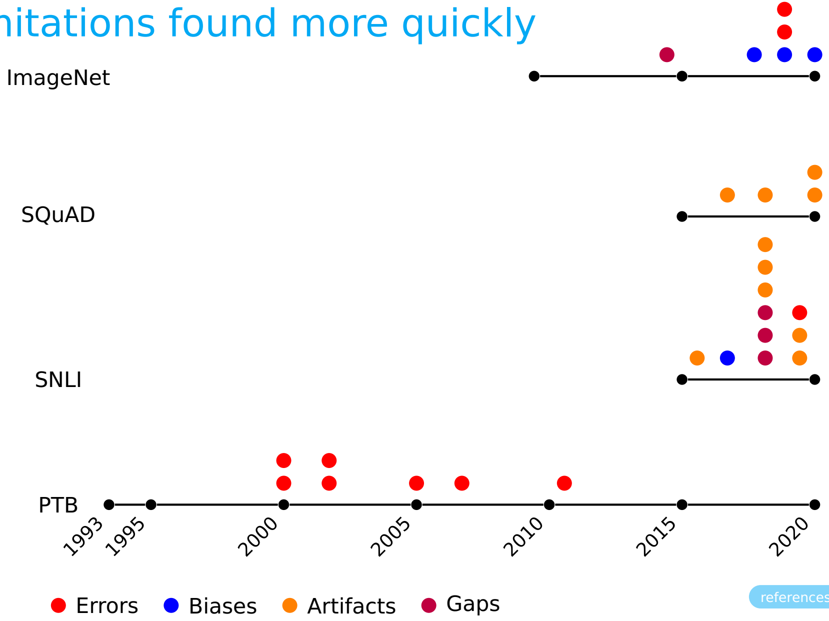

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Two perspectives on dataset creation

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Fixed benchmarks

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Benefits	Drawbacks
Ease of measurement	Community-wide overfitting
Efficiency	Deficiencies inevitable

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Strathern's Law: "When a measure becomes a target, it ceases to be a good measure."

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Can be responsive to evolving needs.

Dynabench

Dynabench: Rethinking Benchmarking in NLP

Douwe Kiela[†], Max Bartolo[‡], Yixin Nie[⋆], Divyansh Kaushik[§], Atticus Geiger[¶], Zhengxuan Wu[¶], Bertie Vidgen[‖], Grusha Prasad[⋆⋆], Amanpreet Singh[†], Pratik Ringshia[†], Zhiyi Ma[†], Tristan Thrush[†], Sebastian Riedel[†‡], Zeerak Waseem[††], Pontus Stenetorp[‡], Robin Jia[†], Mohit Bansal[⋆], Christopher Potts[¶] and Adina Williams[†]

[†] Facebook AI Research; [‡] UCL; [⋆] UNC Chapel Hill; [§] CMU; [¶] Stanford University
[‖] Alan Turing Institute; [⋆⋆] JHU; [††] Simon Fraser University
dynabench@fb.com

Dynabench

Dyna Bench

Rethinking AI Benchmarking

Dynabench is a research platform for dynamic data collection and benchmarking. Static benchmarks have well-known issues: they saturate quickly, are susceptible to overfitting, contain exploitable annotator artifacts and have unclear or imperfect evaluation metrics.

This platform in essence is a scientific experiment: can we make faster progress if we collect data dynamically, with humans and models in the loop, rather than in the old-fashioned static way?

Read more

https://dynabench.org

Dynamics of dynamic datasets

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1. SWAG to BERT to HellaSWAG (Zellers et al. 2018, 2019)

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5. DynaSent (Potts et al. 2021)
6. Dynabench QA

Dataset papers

Gebru et al. 2018; NeurIPS Datasets & Benchmarks track

Dataset papers

1. Standard: Motivation

Gebru et al. 2018; NeurIPS Datasets & Benchmarks track

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   - Reaching the well-intentioned user

Gebru et al. 2018; NeurIPS Datasets & Benchmarks track

Looking back on the SST

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Richard Socher, Alex Perelygin, Jean Y. Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng and Christopher Potts
Stanford University, Stanford, CA 94305, USA
richard@socher.org,{aperelyg,jcchuang,ang}@cs.stanford.edu
{jeaneis,manning,cgpotts}@stanford.edu

Socher et al. 2013

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Healthcare? Professional evaluations? Literary analysis?

Socher et al. 2013

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Healthcare? Professional evaluations? Literary analysis?

Practitioner   Leader

Socher et al. 2013

Assessment

Notions of assessment

Notions of assessment

- Our apparent relentness pursuit of F1 (and friends)

Notions of assessment

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- Empowering users
- Estimating human performance

Metrics and application areas

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- Missing a safety signal costs lives; human review is feasible

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Our (apparent) answer: F1 and friends

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Our (apparent) answer: F1 and friends

Practitioner   Leader

What we seem to value

The Values Encoded in Machine Learning Research

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What we seem to value

Selected 'Values encoded in ML research' from Birhane et al. (2021):

Performance

Efficiency

Interpretability (for researchers)

Applicability in the real world

Robustness

Scalability

Interpretability (for users)

Benificence

Privacy

Fairness

Justice

What we seem to value

Selected 'Values encoded in ML research' from Birhane et al. (2021):

Performance

Towards multidimensional leaderboards

Dodge et al. 2019; Ethayarajh and Jurafsky 2020

Towards multidimensional leaderboards

Dynaboard: An Evaluation-As-A-Service Platform for Holistic Next-Generation Benchmarking

Zhiyi Ma[†*] **Kawin Ethayarajh**[‡*] **Tristan Thrush**[†*] **Somya Jain**[†]

Ledell Wu[†] **Robin Jia**[†] **Christopher Potts**[‡] **Adina Williams**[†] **Douwe Kiela**[†]

[†] Facebook AI; [‡] Stanford University

dynabench@fb.com

Dodge et al. 2019; Ethayarajh and Jurafsky 2020

Towards multidimensional leaderboards

Dynaboard: An Evaluation-As-A-Service Platform for Holistic Next-Generation Benchmarking

Led

DAWNBench: An End-to-End Deep Learning Benchmark and Competition

Cody Coleman, Deepak Narayanan, Daniel Kang, Tian Zhao, Jian Zhang, Luigi Nardi, Peter Bailis, Kunle Olukotun, Chris Ré, Matei Zaharia
Stanford DAWN Project
`http://dawn.cs.stanford.edu/benchmark`

Dodge et al. 2019; Ethayarajh and Jurafsky 2020

Towards multidimensional leaderboards

Dynaboard: An Evaluation-As-A-Service Platform for Holistic Next-Generation Benchmarking

Led

DAWNBench: An End-to-End Deep Learning Benchmark and Competition

Cody Cole

EXPLAINABOARD: An Explainable Leaderboard for NLP

Pengfei Liu[1†], Jinlan Fu[2], Yang Xiao[2], Weizhe Yuan[1], Shuaichen Chang[3], Junqi Dai[2], Yixin Liu[1], Zihuiwen Ye[1], Zi-Yi Dou[1], Graham Neubig[1‡]
[1]Carnegie Mellon University, [2]Fudan University, [3]The Ohio State University,
[†]pliu3@cs.cmu.edu, [‡]gneubig@cs.cmu.edu

Dodge et al. 2019; Ethayarajh and Jurafsky 2020

Dynabench and Dynascore

	8	2	2	2	2	
Model	Performance	Throughput	Memory	Fairness	Robustness	Dynascore
DeBERTa	76.25	4.47	6.97	88.33	90.06	45.92
ELECTRA-large	76.07	2.37	25.30	93.13	91.64	45.79
RoBERTa	69.67	6.88	6.17	88.32	86.10	42.54
ALBERT	68.63	6.85	2.54	87.44	80.90	41.74
BERT	57.14	6.70	5.55	91.45	80.81	36.07
BiDAF	53.48	10.71	3.60	80.79	77.03	33.96
Unrestricted T5	28.80	4.51	10.69	92.32	88.41	22.18
Return Context	5.99	89.80	1.10	95.97	91.61	15.47

Question answering

Ma et al. 2021; https://dynabench.org

Dynabench and Dynascore

Model	Performance	Throughput	Memory	Fairness	Robustness	Dynascore
	8	1	1	5	1	
DeBERTa	76.25	4.47	6.97	88.33	90.06	46.70
ELECTRA-large	76.07	2.37	25.30	93.13	91.64	46.86
RoBERTa	69.67	6.88	6.17	88.32	86.10	43.37
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Question answering

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New directions for neural IR

New directions for neural IR – think of the User!

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When was Stanford University founded?

Term look-up

founded	doc_{47}, doc_{39}, doc_{41}, ...
fountain	doc_{21}, doc_{64}, doc_{16}, ...
⋮	
Stamford	doc_{21}, doc_{11}, doc_{17}, ...
Stanford	doc_{47}, doc_{39}, doc_{68}, ...
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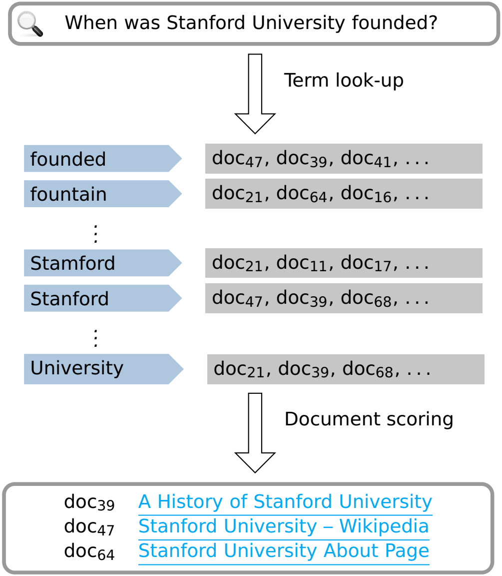
Document scoring

doc$_{39}$	A History of Stanford University
doc$_{47}$	Stanford University – Wikipedia
doc$_{64}$	Stanford University About Page

New directions for neural IR – think of the User!



- ✓ Provenance
- ✓ Updatability
- ✗ Synthesis

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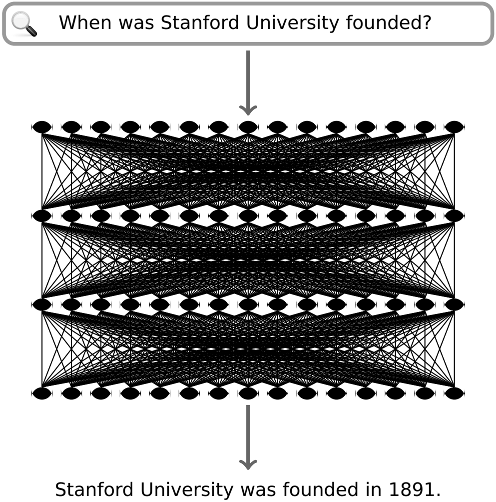

Metzler et al. 2021

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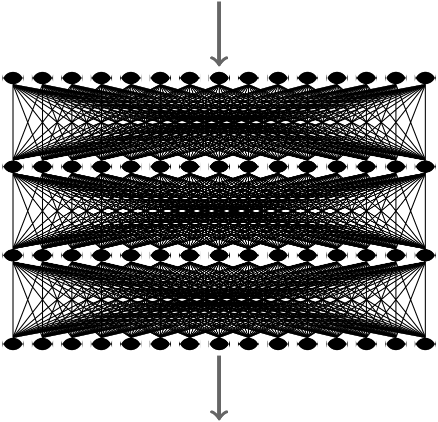

Stanford University was founded in 1891.

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When was Stanford University founded?

Khattab et al. 2021

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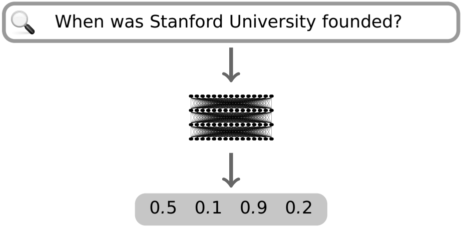

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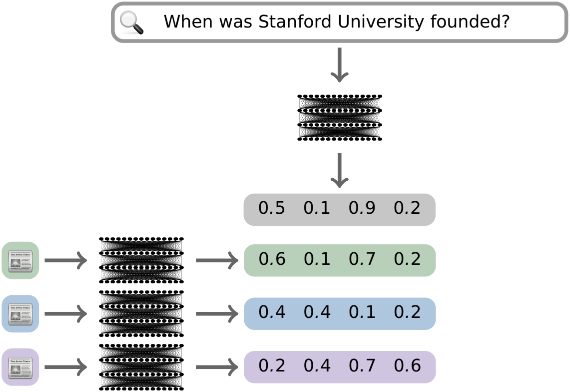

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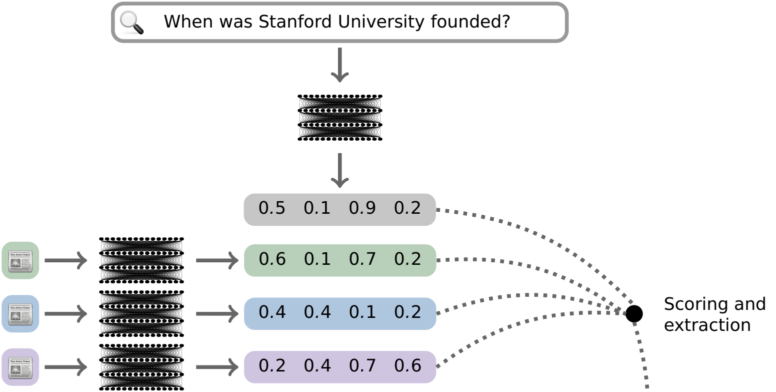

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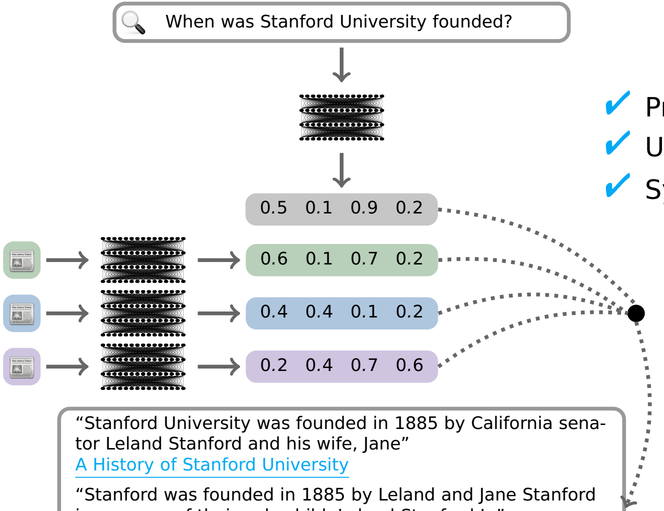

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Khattab et al. 2021

Estimating human performance

Pavlick and Kwiatkowski 2019

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Premise	Label	Hypothesis
A dog jumping	neutral	A dog wearing a sweater

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Human response throughout: “Let’s discuss”

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Human response throughout: “Let’s discuss”

“Human performance” ≈ Average performance of harried crowdworkers doing a machine task repeatedly

Pavlick and Kwiatkowski 2019

Summary

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Assessment today

- One-dimensional
- Largely insensitive to context (use-case)
- Terms set by the research community
- Opaque
- Tailored to machine tasks

Summary

Assessment today

- One-dimensional
- Largely insensitive to context (use-case)
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Assessments in the future

- High-dimensional and fluid
- Highly sensitive to context (use-case)
- Terms set by the stakeholders
- Judgments ultimately made by users
- Tailored to human tasks (?)

Discussion

Opportunities and social responsibilities

- Self-expression
- Language preservation
- Accessibility
- Community building
- Healthcare
- Fraud detection
- Securities trading
- Recommendations
- Advertising
- Surveillance
- Propaganda
- Disinformation

1. Insider: ACL attendee
2. Practitioner: Informed and engaged engineer
3. Leader: Executive with technical training outside of AI
4. User: Someone deriving value from an NLP-driven system

First Rule . . . of many

First Rule . . . of many

Approved and
disapproved uses

First Rule . . . of many

Pernicious
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Approved and
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Pernicious
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Approved and
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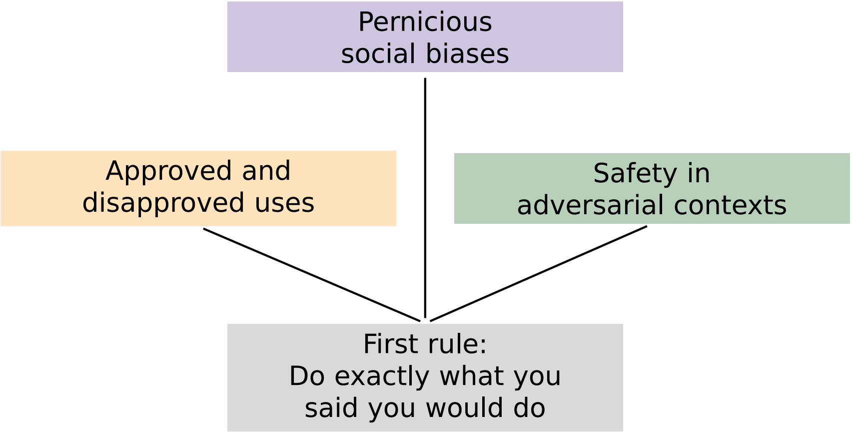
Safety in
adversarial contexts

First Rule . . . of many



Translational research efforts

AI will call for unique solutions, but these examples might be inspiring:

- National Center for Advancing Translational Sciences
- The Translational Research Institute for Space Health
- Mapping Educational Specialist KnowHow (MESH)
- Nutrition labels on foods

(cf. https://datanutrition.org)

Components and consequences

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- Informing well-intentioned potential users of your ideas.

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- Components:

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Thanks!

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References for the benchmark timeline

Penn Treebank (Marcus et al. 1994)

1.	van Halteren 2000	E
2.	Eskin 2000	E
3.	Dickinson and Meurers 2003a	E
4.	Dickinson and Meurers 2003b	E
5.	Dickinson and Meurers 2005	E
6.	Boyd et al. 2008	E
7.	Manning 2011	E

SNLI (Bowman et al. 2015)

1.	Sitzmann et al. 2016	A
2.	Rudinger et al. 2017	S
3.	Naik et al. 2018	G
4.	Glockner et al. 2018	G
5.	Naik et al. 2018	G
6.	Poliak et al. 2018	A
7.	Tsuchiya 2018	A
8.	Gururangan et al. 2018	A
9.	Belinkov et al. 2019	A
10.	McCoy et al. 2019	A

SQuAD (Rajpurkar et al. 2016, 2018)

1.	Weissenborn et al. 2017	A
2.	Sugawara et al. 2018	A
3.	Bartolo et al. 2020	A
4.	Lewis et al. 2021	A

ImageNet (Deng et al. 2009)

1.	Deng et al. 2014	G
2.	Stock and Cisse 2018	B
3.	Yang et al. 2020	B
4.	Recht et al. 2019	E
5.	Northcutt et al. 2021	E
6.	Crawford and Paglen 2021	B

timeline slide