Slow description

On the Opportunities and Risks of Foundation Models

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Digest (of the introduction) by Samuel Albanie, June 2022

This report is the result of a distributed writing effort (spanning many disciplines)

Disclaimer: Not all views expressed in the report are held by all authors

Outline

- What is a foundation model?
- Social impact and ecosystem
- Norms, incentives and the role of academia
- Stanford report on foundation models

What is a foundation model?

Foundation models

A foundation model is a model trained at broad scale that can adapted to a wide range of downstream tasks

Examples: BERT GPT-3 CLIP

The technology is not new:

Self-supervised learning with neural networks

What is new?

Scale and the ability to perform tasks beyond training

Emergence and homogenisation

Two key ideas underpin the significance of foundation models:

Emergence

- system behaviour is implicitly induced rather than explicitly constructed
- cause of scientific excitement and anxiety of unanticipated consequences

Homogenisation

- consolidation of methodology for building machine learning system across many applications
- provides strong leverage for many tasks, but also creates single points of failure

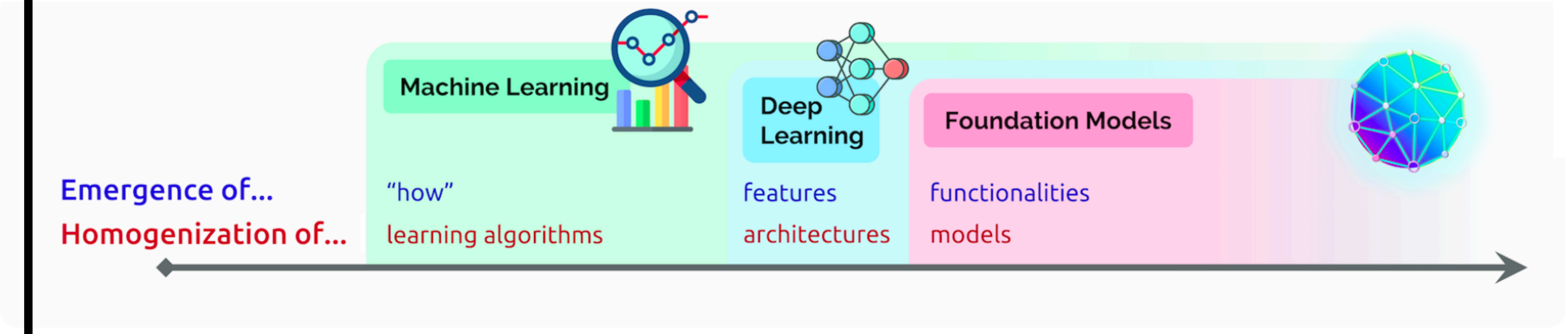

Image credits/References
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Emergence and homogenisation

Machine learning

Modern systems targeting AI tend to use machine learning

The ideas behind machine learning (ML) have been discussed for a long time (Turing, 1948; Samuel, 1959)

Machine learning really began to rise in popularity in 1990s

It represented a shift in how AI systems were built

Machine learning does not specify how to solve a task

Instead, the "how" emerges from the learning process

Machine learning also represents a step towards homogenisation:

Many applications can be powered by the same learning algorithm

Complex tasks in NLP/computer vision still required domain experts

Feature engineering (e.g. SIFT) needed to achieve good performance

Deep Learning

Slightly more than a decade ago, there was a resurgence of Deep Learning

Beyond the original algorithms, key factors included:

- GPUs
- Increased data availability

These produced breakthrough results like AlexNet

Deep learning also represented a shift towards homogenisation:

Instead of hand-crafting features, the same architecture could be used widely

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Foundation models - origin story

Foundation models: origins

Foundation models are enabled by transfer learning (Bozinovski, 1976)

Take knowledge from one task (e.g. object recognition in images) apply it to another task (e.g. activity recognition in videos)

In deep learning, the dominant paradigm is pretraining:

- train a model on a surrogate task
- adapt by fine-tuning on the task of interest

Foundation models are powerful transfer learners due to their scale

Ingredients of scaling:

- computer hardware improvements (e.g. GPUs and memory)
- Transformer architectures (leverage parallelism, expressivity)
- Availability of training data

Foundation models: self-supervision

Transfer learning saw initial success from supervised pretraining (e.g. ImageNet)

However, annotation cost limited its benefits

In self-supervised learning, the pretraining task is derived from the data

Example: BERT is trained to predict a masked word from its context

Build training data: I like brussels sprouts → I like _____ sprouts

Input: I like _____ sprouts → Target: brussels

Self-supervised tasks are more scalable than supervised tasks (no labelling cost)

Also potentially a richer learning signal: the model predicts part of inputs (which can be very diverse), rather than a label space (which is typically more limited)

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Foundation models - NLP developments

Self-supervision in NLP

Self-supervision has been particularly productive in NLP

Word embeddings associate words with context-independent vectors:

- Word representations (Turian et al., 2010)
- word2vec (Mikolov et al., 2013)
- GloVe (Pennington et al., 2014)

Autoregressive language modelling (contextual representations):

- seq2seq pretraining with a language model (Dai et al., 2015)
- GPT (Radford et al., 2018)
- ELMo (Peters et al., 2018)
- ULMFit (Howard et al., 2018)

Transformers: *BERT, GPT-2, RoBERTa, T5, BART*

BERT as an inflection point

Prior to 2019, self-supervised learning was essentially a sub-area in NLP

After 2019, self-supervised language models became a substrate of NLP, with use of BERT becoming the norm

This acceptance of the use of a single model for a wide range of tasks marks the start of the foundation model era

Foundation models produce massive levels of homogenisation

Almost all SotA NLP models are adapted from a handful of sources (BERT, T5 etc.)

Benefit: this provides very high leverage

Improvements in the foundation model yield gains across much of NLP

It also represents a liability

All systems can inherit the biases of a few foundation models

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Foundation models - homogenisation

Homogenisation across research communities

Beyond NLP, increasing homogenisation across communities

Transformer-based sequence models are applied to:

- text (BERT)
- images (ViT)
- speech (Mockingjay)
- tabular data (TaBERT)
- protein sequences (ESM-1b)
- organic molecules (C5T5)
- reinforcement learning (Decision Transformer)

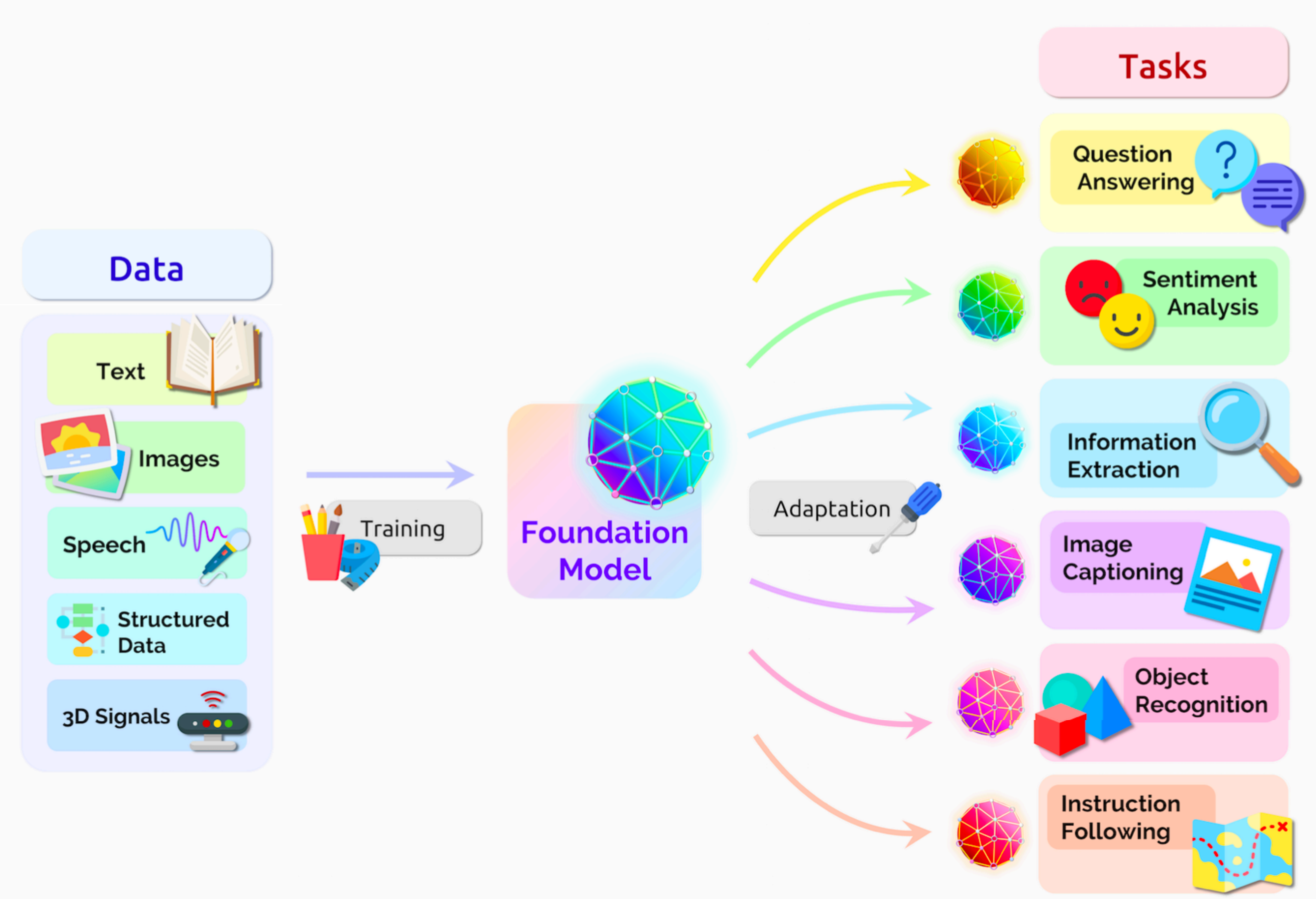
A future of unified tools across modalities?

Homogenisation of models

Homogenisation of individual models across research communities (multimodal models)

Examples in vision and language such as CLIP (Radford et al., 2021), DALL-E (Ramesh et., 2021)

For domains like healthcare, data is naturally multimodal, encouraging multimodal foundation models



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Foundation models - risks and naming

Risks of scale, homogenisation and emergence

Scale has played a key role in the emergence of new abilities

GPT-3 (175B params) enables in-context learning by providing a prompt - emergent property not observed in GPT-2 (1.5B params)

Homogenisation and emergence can interact in an unsettling way

Homogenisation can bring gains where task-specific data is limited

The risk is that flaws are inherited by all adapted models

The power of foundation models comes from emergent properties

They are thus hard to understand/have unexpected failure modes

Since emergence generates uncertainty over capabilities and flaws, aggressive homogenisation is particularly risky

Derisking is the central challenge in developing these models from an ethical and AI safety perspective

The naming of Foundation Models

Bommasani et al. introduce the name "foundation models" to describe the recent paradigm shift

Rationale: **pretrained model** **self-supervised model** describe technical attributes of these models

However, these names do not capture the paradigm shift

language model is too narrow: foundation models go beyond language

general-purpose model **multi-purpose model** capture their flexibility but do not capture their unfinished character and need for adaptation

task-agnostic model captures the manner of training, but not the implications for downstream tasks

foundation models is chosen to describe the emerging paradigm

"Foundation" describes the role these models play: a foundation model is incomplete but serves as a common building block for task-specific models constructed through adaptation

"Foundation" also implies the significance of architectural stability, safety and security:

- well-constructed foundations are a solid bedrock for future applications
- poorly-constructed foundations are a recipe for disaster!

At present, little is known about the nature/quality of the foundation that foundation models provide

Critical problem for researchers, foundation model providers, application developers (who build atop foundation models), policymakers and society at large to address

References

R. Bommasani et al., "On the opportunities and risks of foundation models", arxiv (2021)

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- Norms, incentives and the role of academia
- Stanford report on foundation models

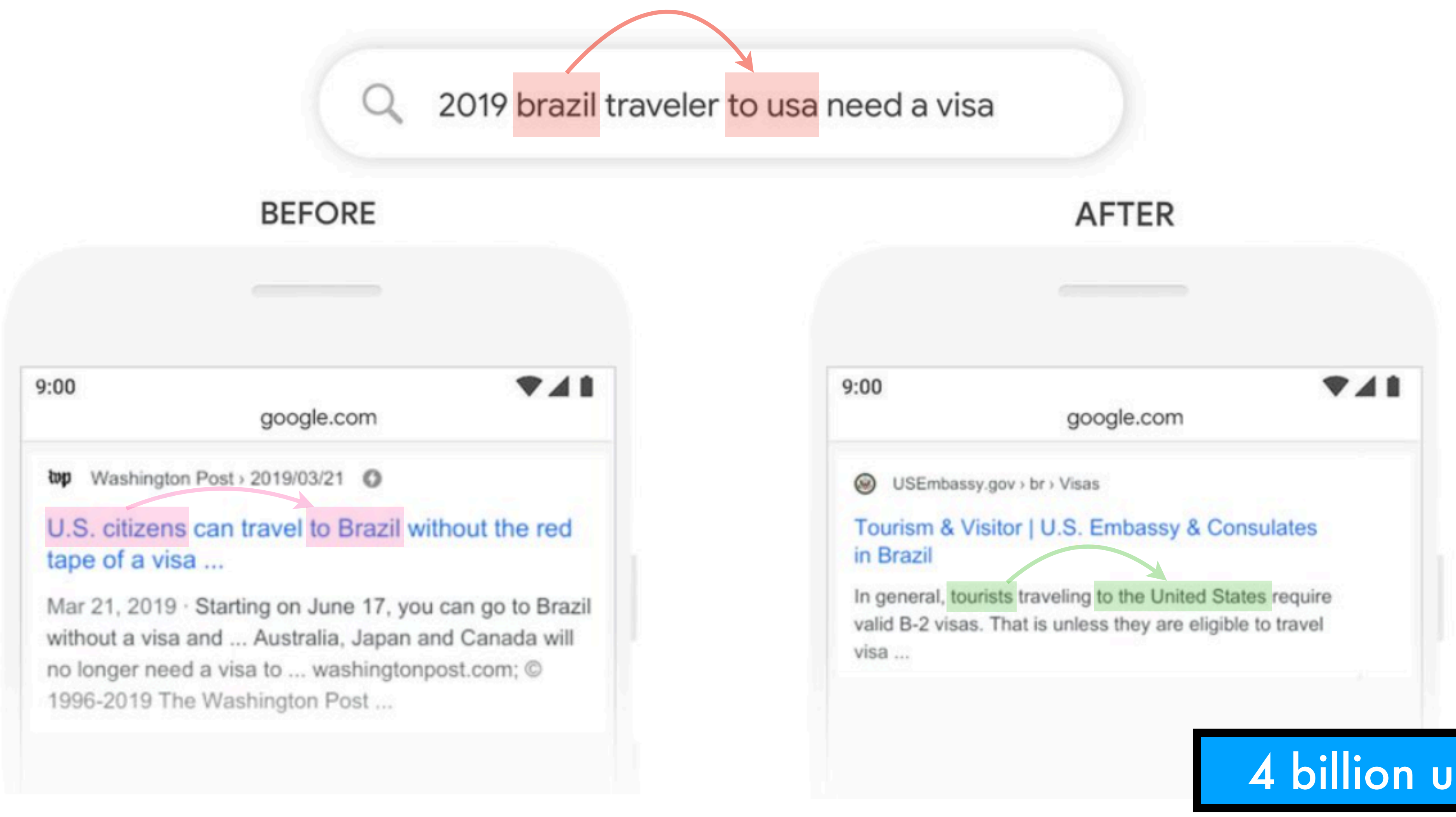
Social impact

Social Impact

Foundation models are scientifically interesting due to their impressive capabilities

But what makes them critical to study is their integration into real-world products

Google search uses models like BERT as a signal



4 billion users

What is the nature of the social impact of foundation models?

How can we responsibly anticipate and tackle ethical/societal considerations?

Note: it is often easiest to reason about specific deployments to specific users

Reasoning about social impact of foundation models in general is challenging

Research vs Deployment

It is useful to distinguish between:

- Research on foundation models
- Deployment of foundation models

Most public knowledge of foundation models comes through model research

academic papers | demonstrations | progress on leaderboards

Direct social impact is driven by deployment (private data/proprietary practices)

Deployments can arise through new products GitHub Copilot (OpenAI Codex)

They can also arise through upgrades to existing products (e.g. Google search)

Research models are typically not extensively tested

They may have unknown failure modes (warning labels can provided)

Deployed foundation models that affect people's lives should be more rigorously audited and tested

Image credits/references:

R. Bommasani et al., "On the opportunities and risks of foundation models", arxiv (2021)

https://blog.google/products/search/search-language-understanding-bert/

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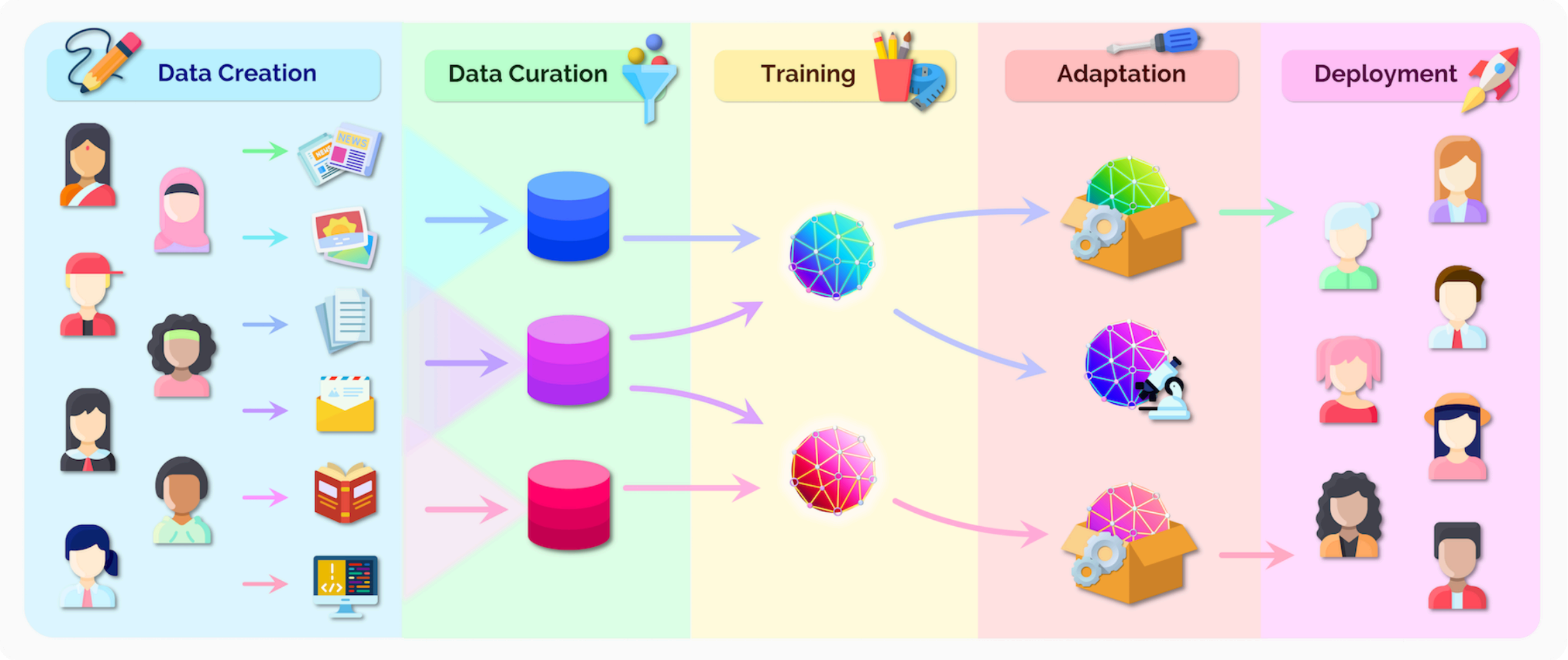
Ecosystem

The foundation model ecosystem

To understand the impact of foundation models (both research and deployment), consider the full ecosystem

The foundation model itself is only one component of an AI system



Adaptation

Adaptation creates a system that performs some task starting from a foundation model

It may combine many modules, rules (e.g. restrictions on output space), classifiers (e.g. for toxicity) etc.

A model that generates toxic content may be tolerable if appropriate precautions are taken downstream

Image credits/references:

R. Bommasani et al., "On the opportunities and risks of foundation models", arxiv (2021)

Data Creation

Heavily human-centric process - most data implicitly about people

Often created by people for other people (emails, photos etc.), measurements of people (e.g. genome), measurements of environments people live in (e.g. satellite images)

All data has an owner and is created with a purpose

The purpose may or may not be to train foundation models....

Data Curation

Data is curated into datasets

There is no single "natural distribution" (selection and filtering)

Ensuring data relevance/quality with legal/ethical compliance is important but often challenging (appreciated in industry)

Training

The celebrated centrepiece of AI research

Deployment

Direct social impact occurs through deployment to people

There may be value in permitting harmful models in research to advance scientific understanding (with appropriate caution)

Staged deployments may partially mitigate harms

Think ecosystem, act model

Ecosystem abstractions

The social impact of foundation models depends on the whole ecosystem

However, it is important to reason about the implications of a single model

Many researchers and practitioners' domain of focus is restricted to the model training stage

It is difficult to reason about model training in isolation because foundation models are unfinished, intermediate objects

By their nature, they can be adapted to downstream tasks (sometimes in unforeseen ways)

Two things can help:

- Surrogate metrics for a representative set of downstream evaluation tasks
- Documenting these metrics (e.g. via Model Cards)

Characterising the full potential downstream social impact of foundation models is challenging

It requires a deep understanding of both the technological ecosystem and of society itself

Image credits/references:
R. Bommasani et al., "On the opportunities and risks of foundation models", arxiv (2021)
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The future of foundation models

Unformed professional norms

Foundation models are in their infancy

Despite deployment, these models are largely research prototypes that are poorly understood

Professional norms ("the ethos of science") are not yet fully developed

There is no consensus on:

when it is "safe" to release foundation models

how the community should respond to methodological misconduct

It is unclear who will determine this consensus

Professional norms - "The Ethos of Science" (Merton)

As noted by Merton in a 1942 essay, "science" is often used to describe:

- a set of characteristic methods by which means of knowledge is certified
- a stock of accumulated knowledge stemming from the application of these methods
- a set of cultural values and mores governing the activities termed "scientific" (or any combination of the above)

The "ethos of science" is the complex of values and norms held to be binding on the scientist

Four institutional imperatives are taken to comprise the ethos of modern science:

1. **Universalism**: truth-claims, whatever their source, are to be subjected to pre-established impersonal criteria

The acceptance or rejection of claims is not to depend on the personal/social attributes of their originator

Science is part of a larger social structure (may conflict with universalism, e.g. in war 1914 "manifesto of the 93")

Pasteur: *"The scientist has a homeland, science does not"*

2. **Communism**: the findings of science are assigned to the community

An eponymous law does is not the exclusive possession of the discoverer

3. **Disinterestedness**: scientists are objective and impartial

Often attributed to personality, can also be understood through the lens of institutional incentives

4. **Organised skepticism**: temporary suspension of judgement and detached scrutiny of beliefs

peer reivew

reproducibility

This is both a methodological and institutional mandate (often bringing science into conflict with other institutions)

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The role of academia and incentives

Industry/Academia

The technology behind foundation models is based on decades of research

This research spans machine learning, NLP, optimisation, computer vision etc.

Contributions have come from both academic and industry labs

Research on building foundation models: almost exclusively in industry

A potential role for academia

The high pace of progress and possibility of centralisation raises issues that may benefit from humanists and social scientists in addition to technologists

Post-hoc audits of ethical/social consequences after design and deployment are insufficient

Ethical design could instead be infused into technological development from the start

Academic institutions typically host the widest set of disciplines under one roof

They bring together computer scientists with economists, legal scholars, ethicists etc.

Academia may therefore have an important role to play in developing foundation models

This role could include: promoting social benefit, mitigating harms, determining boundaries

Incentives

The political economy in which foundation models are developed creates an incentive structure for decision-making at each stage

Market-driven commercial incentives can align well with social benefit

However, they can also lead to underinvestment where shareholders cannot capture the value produced by innovation

The Gates foundation states that in a previous generation, the market for vaccines worked well for wealthy countries, but not for low-income countries

Commercial incentives can ignore social externalities (Reich et al. 2021):

- the health of the informational ecosystem for democracy
- environmental cost of computing resources

There may be little incentive for companies to create an open ecosystem for developing foundation models that encourages broad participation

By contrast, the research mission of universities is the production and dissemination of knowledge/creation of global public goods (Kerr, 2001)

Academia can help to ensure that the development of foundation models is aligned with social benefit that may not be incentivised commercially

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Resource accessibility

Trends in machine learning research

Academia has not participated fully in the development of foundation models

Deep learning has benefited tremendously from increased open science/reproducibility

Public releases of codebases and datasets have become the norm

Open frameworks such as TensorFlow and PyTorch enabled easier sharing of code

Foundation models may roll back this trend

Models may not be released at all (or are restricted to limited API access)

Training of models may be unavailable to AI researchers due to compute costs

Some small scale research feasible thanks to smooth scaling laws (Kaplan et al., 2020)

However, some abilities (like in-context learning) have only been demonstrated at scale

The study of pretrained models can be useful, and has been productive in NLP

But this may be insufficient to address limitations of models arising from design/training

There are community efforts such as EleutherAI and BigScience (hugging face)

But the gap between private/community efforts is likely to grow, rather than shrink

For technologies (as search) centralisation/barrier to entry are potent (K. Radinsky, 2015)

Public infrastructure

It may be possible to close the gap through public infrastructure

We can draw inspiration from:

- Hubble Space Telescope (16B USD in 2021 terms, according to NASA)
- Large Hadron Collider (budget of 9B USD, as of 2010)

There is a US National Research Cloud initiative underway

Volunteer computing

Donated compute from volunteers across many nodes can be effective

Folding@home illustrated value for protein dynamics (Beberg et al., 2009)

Learning@home is exploring similar ideas for foundation models

This approach faces major technical challenges (latency, bandwidth)

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A Report on Foundation Models

Overview of the Stanford report

In March 2021, an informal community at Stanford of students, faculty and researchers with interest in some element of foundation models was created

Not just AI researchers, but also experts in healthcare, law, ethics, economics etc.

Led to the founding of the Center for Research on Foundation Models (CRFM) at Stanford

Given gaps in mutual understanding and existing literature, that goal was to:

- provide a fuller picture of foundation models
- identify opportunities and risks of foundation models
- establish a constructive vision for future responsible development of foundation models

The report writing was an experiment with over 100 people from different backgrounds

Much of the report is a survey of existing work that is unified to highlight connections

The report focuses on four themes relating to foundation models:

capabilties | applications | technology | society

Caveats: field is evolving rapidly, so much of the coverage is inevitably incomplete

Many applications are discussed, but others (e.g. music, agriculture, finance, natural sciences) are omitted

Other directions (applications to neuroscience, psychology etc.) form possible future work

Disclaimer: Not all views expressed in the report are held by all authors

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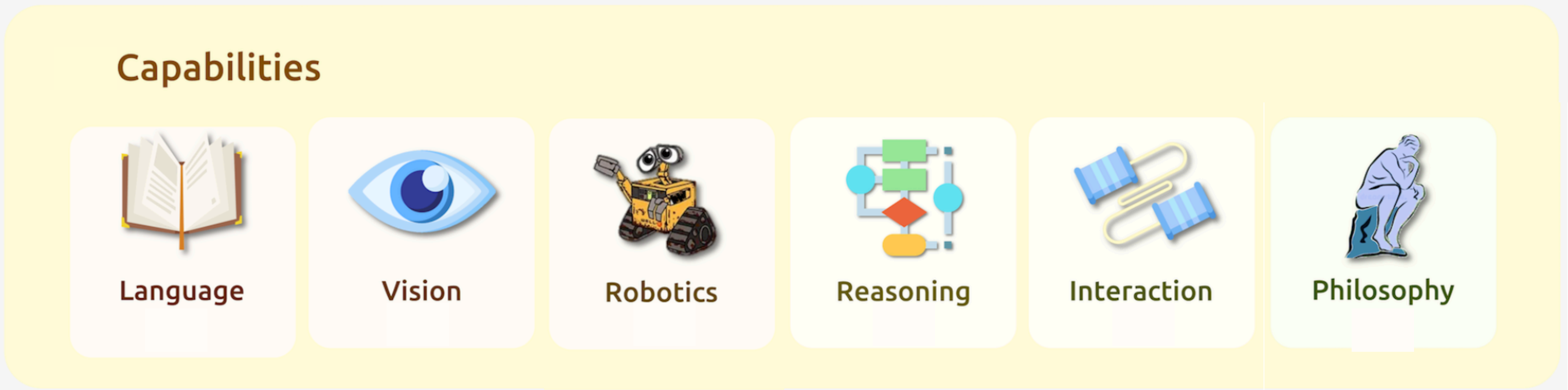
Capabilities



Language

Foundation models dominate NLP benchmarks

There is still a gap between current abilities and humans

Gap can be studied through lens of linguistic variation

Variation includes different styles, dialects, languages

Children more sample efficient than foundation models

Multimodal signals/grounding may bridge the gap

Vision

Computer vision led adoption of deep learning

Demonstrated benefits of pretraining (e.g. ImageNet)

CLIP showed major gains from internet scale image+text

Multimodal/embodied data may enable further progress

Key challenges in modelling (e.g. videos) & evaluation

Applications (healthcare) and society (surveillance)

Robotics

Longstanding goal: "generalist robots" for many tasks

Robotics is anchored to the physical world

Key challenge: sufficient data of the right form

Foundation models may allow easier specification and learning of tasks by robots

Applications (e.g. household); robustness and safety

Reasoning and search

Theorem providing/program synthesis - classic problems

Combinatorial search space means traditional search-based methods are typically intractable

AlphaGo shows deep networks can guide search space

Humans also efficiently transfer knowledge across tasks

Foundation models may help close this gap

Interaction

Foundation models lower difficulty threshold for prototyping and building AI applications

They raise the ceiling for novel user interaction

This suggests a synergy:

- developers can provide applications that better fit the user's needs and values
- also introduce more dynamic interaction/feedback

Philosophy

What could a foundation model understand about the data it is trained on?

For natural language, different positions can be taken

Tentative conclusion: skepticism about the capacity of future models to understand language may be premature

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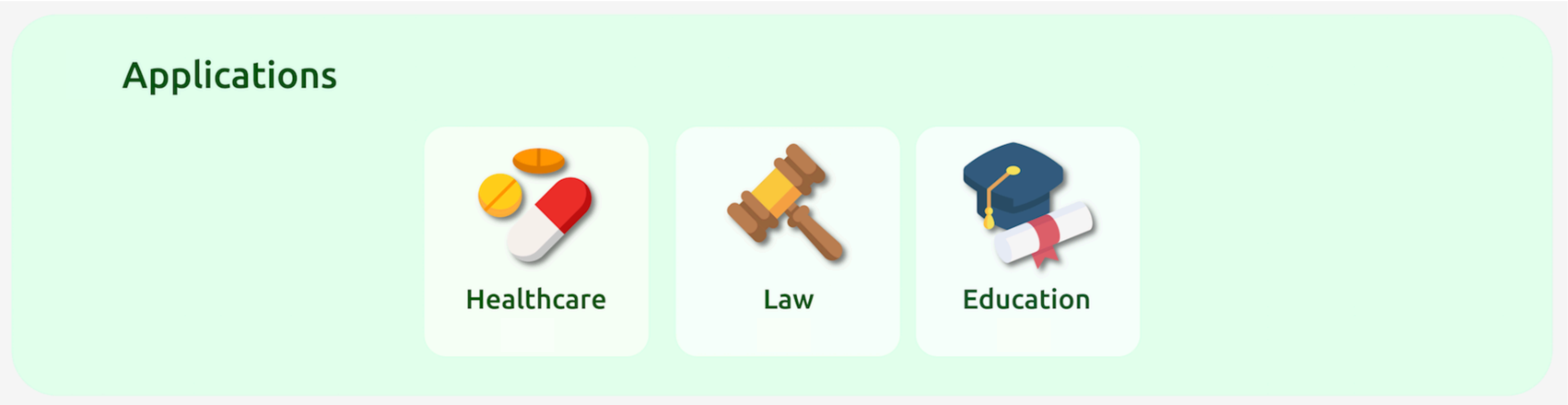
Applications



Healthcare and biomedicine

Many tasks require expert knowledge that is costly:

- Healthcare tasks (e.g. disease treatment)
- Biomedical research (e.g. discovery of new therapies)

Foundation models may be able to learn from data across modalities (images, text, molecules)

Could yield benefits in improved sample efficiency

May also allow improved interface design

This could allow patients/providers to interact with AI

Generative abilities of foundation models have potential for open-ended research problems (e.g. drug discovery)

Foundation models also bring risks (e.g. exacerbating historical biases in medical datasets/trials)

Challenges: data sources and privacy (sociotechnical)

Model interpretability and explainability; regulation

Law

Attorneys devote effort to producing coherent narratives and deciphering ambiguous legal standards

Foundation models may provide benefits:

- Legal documents provide data to train on
- Generative abilities could map to generative legal tasks

However, major progress is needed to enable:

- reliable reasoning over multiple sources of information
- generation of truthful long-form documents

Sample efficiency is valuable due to cost of legal experts

Could enable reallocation of resources to justice/service

As with healthcare, privacy will be a key concern

Fundamental advances will be required with respect to:

- provenance of behaviour
- guarantees for factuality of generation

Education

Effective teaching requires reasoning about student cognition and must reflect the learning goals of students

Models may use external information and modalities (textbooks, diagrams, videos) to assist learning:

- generative tasks (problem generation)
- interactive tasks (feedback to teachers)

Sample efficiency may enable adaptive/personalised learning content

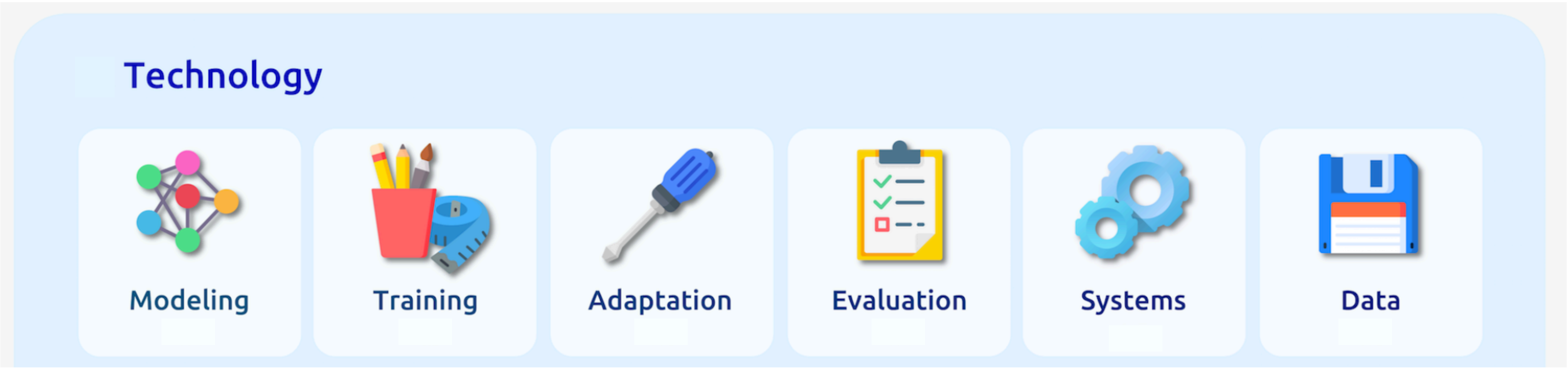
Student privacy will then become a key issue

Other factors also become more critical:

- unequal access to technology in education
- technology-aided plagiarism

Image credits/References:
R. Bommasani et al., "On the opportunities and risks of foundation models", arxiv (2021)

Technology



Modelling

5 key attributes underly foundation model architectures:

- Expressivity - ability to assimilate real-world information
- Scalability - handling large quantities of high dim. data
- Multimodality - consume/produce over modalities
- Memory - effective knowledge storing and retrieval
- Compositionally - generalisation to novel scenarios

Adaptation

Foundation models are "unfinished" assets

Adaptation strategies: fine-tuning, prompting

Adaptation can go beyond task specialisation:

- alleviate deficiencies (temporal adaptation)
- constraints (e.g. right to be forgotten under GDPR)

Expansive evaluation protocols will be required

Systems

Computer systems are a bottleneck in scaling up data/ model size, which appear to correlate with performance

The next generation of foundation models will require co-design of hardware, software, models and algorithms

Co-design is emerging (e.g. retrieval-based architectures)

Practical deployment requires efficient inference

Training

Status quo for training: modality-specific objectives

Masking text (BERT); augmented images (SimCLR)

Future training objectives may involve:

- principled selection (a systematic approach)
- domain generality (unified training across sources)

Key design trade-offs (generative/discriminative); goals

Evaluation

Foundation models: 1 step removed from specific tasks

New paradigms for evaluation may consider:

- directly measuring inherent capabilities
- adaptation when by controlling for access/resources
- broader evaluation (robustness, fairness, efficiency, environmental impact)

Data

Training data is integral to foundation model abilities

The criticality of data is emphasised in data-centric AI

Models have not had much transparency over data

One path forwards data hub for foundation models

Consideration must be given to selection, curation, documentation, access, visualisation, quality, regulation

Image Credits/References:

R. Bommasani et al., "On the opportunities and risks of foundation models", arxiv (2021)

(BERT) J. Devlin et al., "Bert: Pre-training of deep bidirectional transformers for language understanding", NAACL-HLT (2019)

(SimCLR) T. Chen et al., "A simple framework for contrastive learning of visual representations", ICML (2020)

C. Ré, The Road to Software 2.0 or Data-Centric AI https://hazyresearch.stanford.edu/data-centric-ai (2021)

Technology

Security

Foundation models may form a single point of failure

Discovered security vulnerabilities (adversarial triggers)

Privacy risks (e.g. memorisation of training data)

Generality poses risks for function creep (unintended use)

One view: foundation models as operating systems

Privacy: public data may reduce need for sensitive data

Robustness to distribution shifts

Typical ML models are highly sensitive to distribution shift

Foundation models trained on broad data collections appear to offer greater robustness to distribution shifts

However, they are not a panacea for robustness

Key challenges include: extrapolation across time and spurious correlations derived from the training data

AI Safety and Alignment

In deployment, it is more important that models are:

- reliable
- robust
- interpretable

Task: align models to avoid misspecified goals/values

Task: Forecast emergent behaviours (ability to deceive)

Theory

The study of foundation models is largely empirical

Supervised theory is inadequate, due to the discrepancy between training/adaption phases

Advances in theory to address this discrepancy may yield useful insights

Interpretability

Most interpretability methods focus on explaining the behaviour of task-specific models

Foundation models span tasks (introducing challenges)

One lens: the one model-many models paradigm

Goal: find extent that the one model (foundation) and its many models (adapted) share decision-making blocks

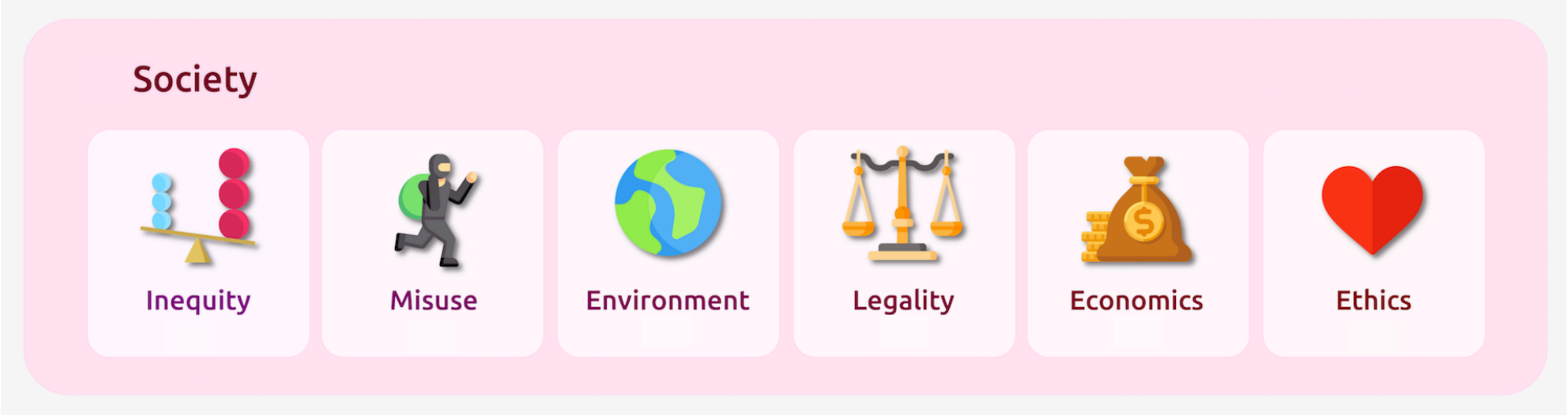
Key concepts for interpretability:

- explainability (validity of post hoc explanations)
- mechanisms that drive model behaviour

It is also valuable to consider the societal impact of interpretability and non-interpretability

Image credits/References:
R. Bommasani et al., "On the opportunities and risks of foundation models", arxiv (2021)

Society



Inequity and fairness

ML can contribute to and amplify social inequity

For foundation models, it is useful to separate:

- intrinsic biases (properties in the foundation model)
- extrinsic harms (harms in specific applications)

Source tracing to understand ethical/legal responsibility

Mitigations: proactive interventions/reactive recourse

Environment

Foundation models involve significant training/emissions

One perspective: amortised cost over re-use

Several factors would be beneficial to consider:

- compute-efficient models, hardware, energy grids
- environmental cost as a factor for evaluation
- greater documentation and measurement

Economics

Foundation models may have economic impact due to:

- novel capabilities
- potential applications in wide array of industries

Initial analyses have been conducted to understand implications for productivity, wage inequality, concentration of ownership

Misuse

Misuse: the use of foundation models as technically intended but for societal harm (e.g. disinformation)

Foundation models may make misuse easier by generating high-quality personalised content

Disinformation actors can target demographic groups

Foundation models may also help to detect misuse

Legality

How law bears on development/deployment is unclear

Legal/regulatory frameworks will be needed

In the US setting, important issues include:

- liability for model predictions
- protections from model behaviour

Legal standards must advance for intermediate models

Ethics of scale

Widespread adoption of foundation models poses ethical, political and social concerns

Ethical issues related to scale:

- homogenisation
- concentration of power

How can norms and release strategies address these?

Image credits/References:

R. Bommasani et al., "On the opportunities and risks of foundation models", arxiv (2021)

Responses/critiques

Blodgett & Madaio - "risks in education"

Foundation models may bring benefits, but risk harms

Four risks in an educational setting:

Risks of educational technologies at scale

arguments for student benefit often motivate surveillance

historically, scaling has not benefited all learners

Technology (e.g. TV, computers) has second-order effects

Risks of homogenisation

Homogenisation of pedagogy, ideology, content

Data may dictate ideology about what is valuable

Risks of limited roles of stakeholders in design

At odds with educational philosophy (learners' interests shape teachers' choices about what and how to teach)

Risks of totalising visions of models in education

Formalising learning such that it is legible to these models

Malik - "castles in the air"

Clearly, these models have been useful (e.g. BERT)

The pretrain and fine-tune paradigm has merits

There are big risks with training on uncurated data

The name "foundation models" suggests that these models provide a template for all of AI research

Subscribes to embodiment hypothesis (cognitive science)

"..intelligence emerges in the interaction of an agent with an environment and as the result of sensorimotor activity...." (Smith et al., 2005)

Not arguing for only following human development

But interaction, grounding, acting in a physical world etc. are important parts of AI

Foundation models at present are "castles in the air"

Strategy: avoid over-investing in current paradigm

Marcus & Davis - "A new foundation?"

Foundation: bedrock on which something complex is built

Programmers can build on an OS with reliability below

A foundation for AI should provide something similar:

reliable use of information, reliable reasoning etc.

But we have stochastic parrots (Bender et al., 2021)

Good at mimicry, but lack depth of understanding

Five serious concerns:

- Unjustified renaming of pretrained language models
- Limited scientific argument (lack of concrete proposals)
- "Not invented here" attitude
    - little discussion of work from relevant fields
    - other machine learning ideas in the "scrap heap"
- Actual impact of foundation models so far is modest
- Actively promotes tunnel vision (Bender, 2021)

References:

S. L. Blodgett and M. Madaio., "Risks of AI foundation models in education", arxiv (2021)

(Malik) https://crfm.stanford.edu/commentary/2021/10/18/malik.html

(BERT) J. Devlin et al., "Bert: Pre-training of deep bidirectional transformers for language understanding", NAACL-HLT (2019)

L. Smith and M. Gasser, "The development of embodied cognition: Six lessons from babies", Artificial life (2005)

https://crfm.stanford.edu/commentary/2021/10/18/marcus-davis.html

E. M. Bender et al., "On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?", FAccT (2021)

(Bender, 2021) https://twitter.com/emilymbender/status/1430944351358648324

Responses/critiques

Sastry - "beyond release/not release"

Discussion has focused on release vs not release

There may be other options in the release design space

Different APIs take different approaches:

- (OpenAI) text in & text out
- (Cohere) access to text embeddings

Exposing model guts brings risks and requires trust

Increases the risk of model stealing attacks

This could defeat the goal of constraining access

For healthy governance, we need ways to:

- audit models
- audit the audits

Research into release design space would be valuable

Steinhardt - "risks of emergent behaviour"

Push emergence/homogenisation further to logical conclusions

The report's use of "emergence" fits self-organising systems

Different definition: qualitative changes arising from quantitative parameter change ("More is different", Anderson 1972)

Applies to both self-organising systems and physical systems

Phase changes: behaviour manifests quickly at thresholds

We should expect behaviour to emerge routinely (and suddenly)

Capabilities like hacking may emerge with little time to respond

Misaligned objectives: deceptive behaviour may also emerge

Homogenisation contributes to inertia, slowing responses

Institutions can takes years/decades to respond to technology

When problems are clear, we will be fixing a rocket as it takes off

Alternative: fix rocket while it's on the launchpad (think ahead)

Forecasting AI (Steinhardt, 2021) - can help build a picture

Mitigation strategies alignment (Hendrycks et al., 2021)

References:
https://crfm.stanford.edu/commentary/2021/10/18/sastry.html
(Steinhardt) https://crfm.stanford.edu/commentary/2021/10/18/steinhardt.html
P. Anderson, "More is different: broken symmetry and the nature of the hierarchical structure of science", Science (1972)
(Steinhardt forecasting) https://bounded-regret.ghost.io/ai-forecasting/ (2021)
(Steinhardt ML safety) D. Hendrycks et al., "Unsolved problems in ml safety", arxiv (2021)

Summary and further resources

Summary

A foundation model is a model trained at broad scale that can adapted to a wide range of downstream tasks

Characteristics: emergence and homogenisation

These models may have significant societal impact

The professional norms are not yet fully formed

Development has been led by industry rather than academia

Further resources

The full Stanford report on foundation models

Workshop with talks and panel discussions on:

- Opportunities and Responsibilities
- Technological Foundations
- Industry and Applications
- Harms and Societies

References:

R. Bommasani et al., "On the opportunities and risks of foundation models", arxiv (2021)

Workshop on Foundation Models: (Welcome and Introduction): https://www.youtube.com/embed/RLrjKGN89Fc

Workshop on Foundation Models Session I: (Opportunities and Responsibilities): https://www.youtube.com/embed/Iux1MExMIAk

Workshop on Foundation Models Session II: (Technological Foundations): https://www.youtube.com/embed/PNTbvoweqBk

Workshop on Foundation Models Session III: (Industry and Applications): https://www.youtube.com/embed/du1YiytHwXs

Workshop on Foundation Models Session IV: (Harms and Society): https://www.youtube.com/embed/T2e6Y37EAGo