## Al Safety and the Life Sciences

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- Claim 1: The life sciences will drive the next decade of creativity in Al
  - Economic and social incentives
  - Rich multi-modal data scaling at high exponential rates
  - Challenging biomedical problems
- Claim 2: Integrating AI safety and the life sciences is critical and will require significant transdisciplinary efforts



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  - Economic and social incentives



## Deloitte.

## 2019 Global Life Sciences Outlook

Focus and transform | Accelerating change in life sciences

Global health care spending continues to increase dramatically



is projected to reach

\$10.059 trillion by 2022



## THE KEY TO SUCCESSFUL DIGITAL TRANSFORMATION IN LIFE SCIENCES





### cisco

## Digital Transformation for Life Sciences

Cisco Healthcare is empowering innovation. Our technologies make it possible to improve customer engagement, reduce discovery and development time, transform the global supply chain, and address changes in the global and regulatory environment, all while enabling security and compliance.







#### **R&D** and Clinical Trials

- · Collaboration video, voice, and virtual meetings
- · Cloud and data center
- Data virtualization
- Analytics
- Asset management
- · Customer-contact center

#### **Manufacturing and Supply Chain**

- Unified, converged factory network
- · Connected machines and edge computing
- · Centralized, pervasive wireless
- Analytics
- · Services-exchange platform
- · Asset management

#### **Marketing and Sales Engagement**

- · Collaboration video, voice, and virtual meetings
- Automated response bots
- · Customer-contact center
- Analytics



# Top 3 Digital Transformation Challenges in Life Sciences

**LEARN MORE** 

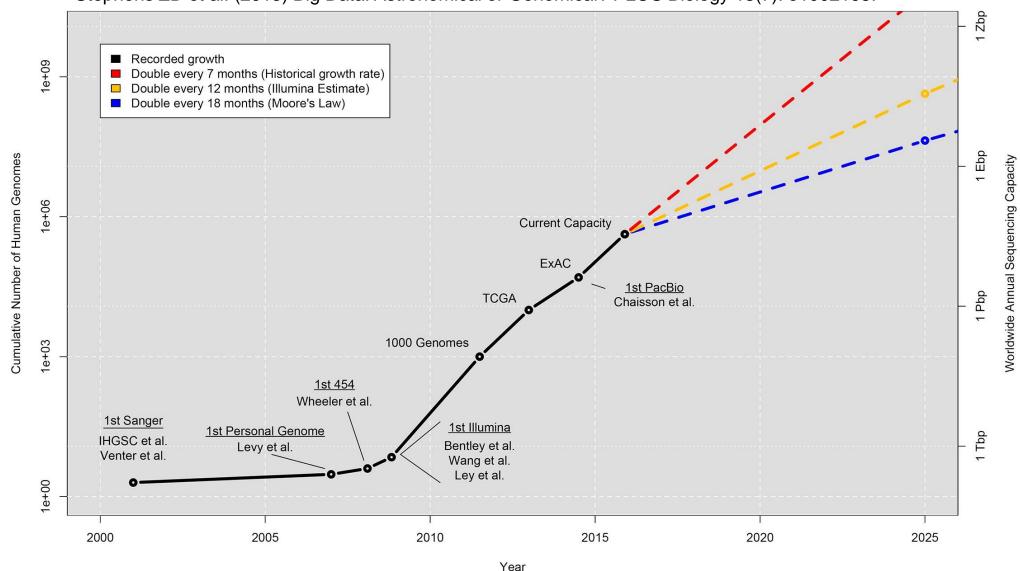


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  - Challenging biomedical problems



## Scaling of DNA Sequencing

Stephens ZD et al. (2015) Big Data: Astronomical or Genomical? PLOS Biology 13(7): e1002195.





## Bio-inspired AI: Uncovering the Genomic Basis of Disease



- Open-source, genomic analysis platform
- MatrixTable: first-class support for multi-dimensional structured data, built from the ground-up as a distributed system running in the cloud
- The structure, scale, and analyses of genomic data inspired a new distributed data structure that is broadly useful in biology and beyond



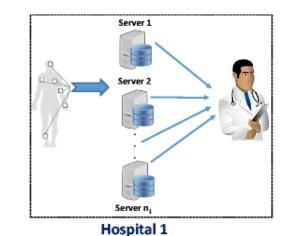


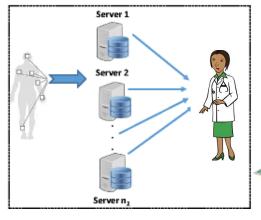
## Bio-Inspired AI: Secure Multi-Party Linear Regression

J. Bloom "Secure multi-party linear regression at plaintext speed." *arXiv preprint* arXiv:1901.09531 (2019).

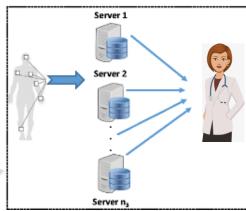
B. Berger and H. Cho "Emerging technologies towards enhancing privacy in genomic data sharing" *Genome Biology* (2019)

- Secure multi-party regression at plain text speed
- Addresses issues of data ownership, transmission, and storage at scale



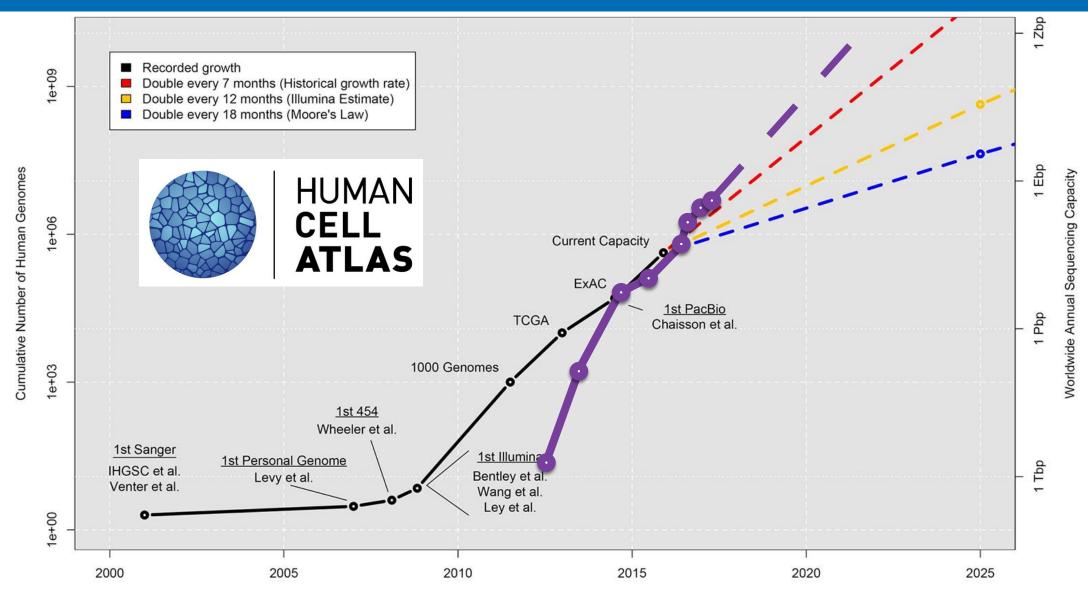








## Scaling of Cells Profiled at the Klarman Cell Observatory



Year

## Bio-Inspired AI: Representation Learning of scRNA Data







#### Loss Landscapes of Regularized Linear Autoencoders

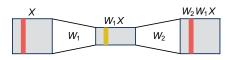
Daniel Kunin\*1,2, Jonathan M. Bloom\*1, Aleksandrina Goeva1, Cotton Seed1





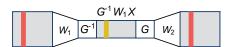
#### Background

A linear autoencoder maps  $R^{m_1}$   $R^{k_1}$   $R^{m_2}$ 



$$L(W_1, W_2) = ||X - W_2 W_1 X||^2$$

LAEs learn the top principal subspace but not the principal directions or eigenvalues. The optimal latent representation is only defined up to a linear map  $G \supseteq GL_k(R)$ .



LAEs are pseudoinverses at all critical pts.

#### Regularization

We prove that L2-regularized LAEs are transposes at all critical points and learn the principal directions as the left singular vectors of the decoder. Define  $L_{\sigma}$  by

$$||X - W_2 W_1 X||^2 + \lambda(||W_1||^2 + ||W_2||^2)$$

The minima of  $L_{\sigma}$  are defined up to an orthogonal map  $O 2 O_k(R)$  by

$$W_2 = U_k(I - \lambda_k^{-2})^{\frac{1}{2}}O = W_1^{|}$$

where  $X = U^{\wedge} V^{T}$  and  $\sigma_{1}^{2} > \cdots > \sigma_{k}^{2} > \lambda$ .

$$W_2W_1 = U_k(I - \lambda^{-2})U_k^{l}$$

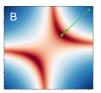
#### PCA Algorithms

Hence PCA is a two-step optimization:

- 1. Train L<sup>2</sup>-regularized LAE on  $X \rightarrow \mathbb{R}^{m \rightarrow n}$ .
- 2. Apply SVD to the decoder  $W_2 \rightarrow \mathbb{R}^{m \rightarrow k}$ .

Step 2 is quick. Step 1 options include:

- A. Gradient descent (below).
- B. Solve for  $W_2$ , set  $W_1 = W_2^1$ , iterate.

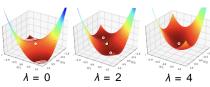


input  $X \in \mathbb{R}^{m \times n}$ ; k < m;  $\lambda, \alpha > 0$ initialize  $W_1, W_2^{\mathsf{T}} \in \mathbb{R}^{k \times m}$ while not converged  $W_1 = \alpha \left( W_2^{\mathsf{T}} (W_2 W_1 - I) X X^{\mathsf{T}} + \lambda W_1 \right)$ 

 $W_2 = \alpha \left( (\tilde{W}_2 W_1 - I) X X^{\mathsf{T}} W_1^{\mathsf{T}} + \lambda W_2 \right)$  $U, \Sigma, \_ = SVD(W_2)$ return  $U, \lambda(I-\Sigma^2)^{-1}$ 

#### Posterior Collapse

Principal directions with eigenvalues below  $\lambda$  collapse as in probabilistic PCA.



Example of collapse for X = [2]

#### Symmetry and Backprop

L2-reg LAEs are symmetric at all critical pts.

Theorem 2.1 (Transpose Theorem). All critical points of  $\mathcal{L}_{\sigma}$  satisfy  $W_1 = W_2^{\uparrow}$ .

*Proof.* Critical points of  $\mathcal{L}_{\sigma}$  satisfy:

$$\begin{split} \frac{\partial \mathcal{L}_{\sigma}}{\partial W_{1}} &= 2W_{2}^{\mathsf{T}}(W_{2}W_{1} - I)XX^{\mathsf{T}} + 2\lambda W_{1} = 0, \\ \frac{\partial \mathcal{L}_{\sigma}}{\partial W_{2}} &= 2(W_{2}W_{1} - I)XX^{\mathsf{T}}W_{1}^{\mathsf{T}} + 2\lambda W_{2} = 0. \end{split}$$

We first prove that the matrix

$$C = (I - W_2W_1)XX^{\mathsf{T}}$$

is positive semi-definite<sup>8</sup>. Rearranging  $\frac{\partial \mathcal{L}_{\sigma}}{\partial W_{\sigma}} W_2^{\mathsf{T}}$  gives

$$XX^\intercal(W_2W_1)^\intercal = (W_2W_1)XX^\intercal(W_2W_1)^\intercal + \lambda W_2W_2^\intercal.$$

Both terms on the right are positive semi-definite, so their sum on the left is as well and therefore

$$XX^{\intercal}(W_2W_1)^{\intercal} \succeq (W_2W_1)XX^{\intercal}(W_2W_1)^{\intercal}.$$

Cancelling  $(W_2W_1)^{\mathsf{T}}$  via Lemma B.1 gives  $C \succeq 0$ .

We now show the difference  $A = W_1 - W_2^{\mathsf{T}}$  is zero. Rearranging terms using the symmetry of C gives

$$0 = \frac{\partial \mathcal{L}_{\sigma}}{\partial W_1} - \frac{\partial \mathcal{L}_{\sigma}}{\partial W_2}^{\mathsf{T}} = 2A(C + \lambda I).$$

Since  $C \succeq 0$  and  $\lambda > 0$  imply  $C + \lambda I \succ 0$ , we conclude

$$A(C + \lambda I)A^T = 0$$

that A=0.

Resolution to weight transport problem:



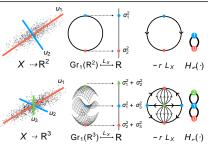
Backprop in lacks W because neurons go one way.

Learn as W2 by maximizing flow of info and minimizing energy.

#### Algebraic Topology

We smoothly parameterize the critical manifolds of LAEs with several forms of regularization via one elementary proof.

We factor the loss as a Morse function on the Grassmannian to reveal the dynamics near and between critical manifolds. Morse homology suggests principles and algorithms for deep learning.



Theorem 4.4 (Curvature Theorem). In local coordinates near any point on the critical manifold indexed by I, all three losses take the form of a standard degenerate saddle with  $d_{\mathcal{I}} + (k - \ell)(m - \ell)$  descending directions.

- L and L= have kl flat directions.
- L<sub>σ</sub> has kℓ − (<sup>ℓ+1</sup>) flat directions. The remaining directions are ascending.

**Theorem E.1.**  $\mathcal{L}_X$  is an  $\mathbb{F}_2$ -perfect Morse function. Its critical points are the rank-k principal subspaces.

Proof. Consider the commutative diagram

$$V_{k}(\mathbb{R}^{m}) \xrightarrow{\pi:O \to \operatorname{Im}(OO^{\intercal})} \operatorname{Gr}_{k}(\mathbb{R}^{m})$$

$$\iota:O \to (O^{\intercal},O) \downarrow \qquad \qquad \downarrow \mathcal{L}_{X} \qquad (10)$$

$$\mathbb{R}^{k \times m} \times \mathbb{R}^{m \times k} \xrightarrow{\mathcal{L}} \mathbb{R}$$

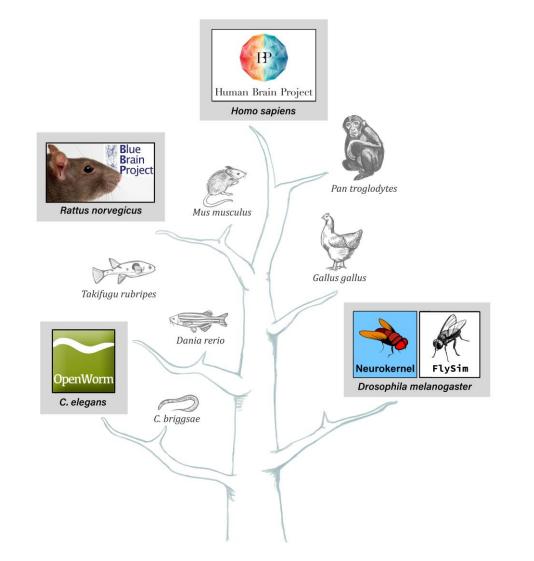
MiA talks at <u>broadinstitute.org/mia</u>



## Bio-Inspired AI: Realistic Nervous System Simulations

G. Sarma, A. Safron, and N. Hay, "Integrative Biological Simulation, Neuropsychology, and Al Safety." AAAI Workshop on Al Safety (2019)

- Simple organisms show complex behavior that continues to be difficult for modern AI systems.
- Neuronal simulations in virtual environments will allow these biological architectures to be used for AI research.



**NEURON** 

BluePyOpt

**NetPyNE** 

**Bionet** 

Geppetto

ChannelPedia

**NeuroMLDB** 



















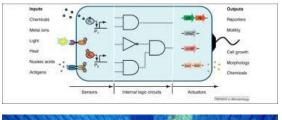
insitro (Roche) BenevolentAl

## Verily ROIVANT H V & E V GINKGO BIOWORKS THE ORGANISM COMPANY Y Combinator







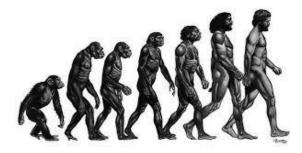


















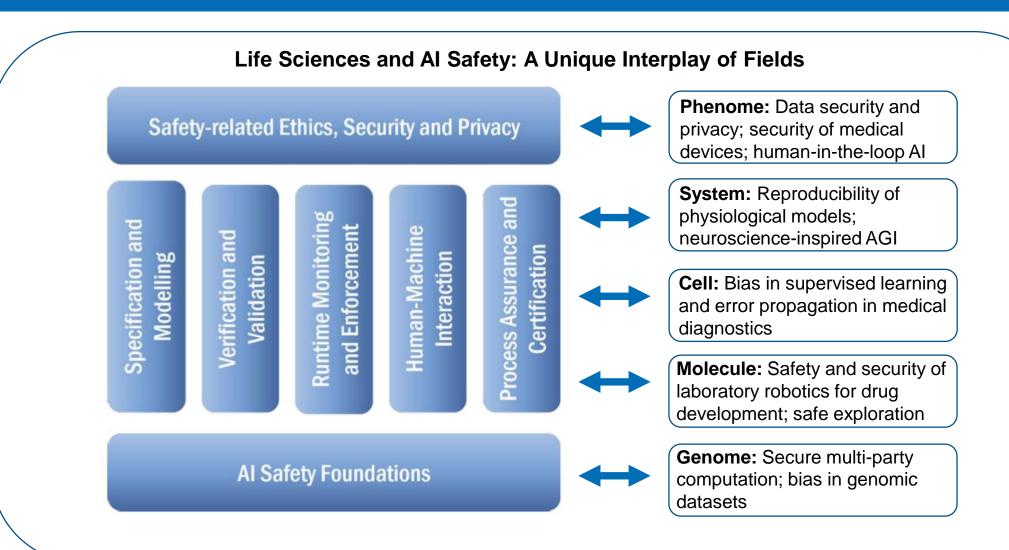


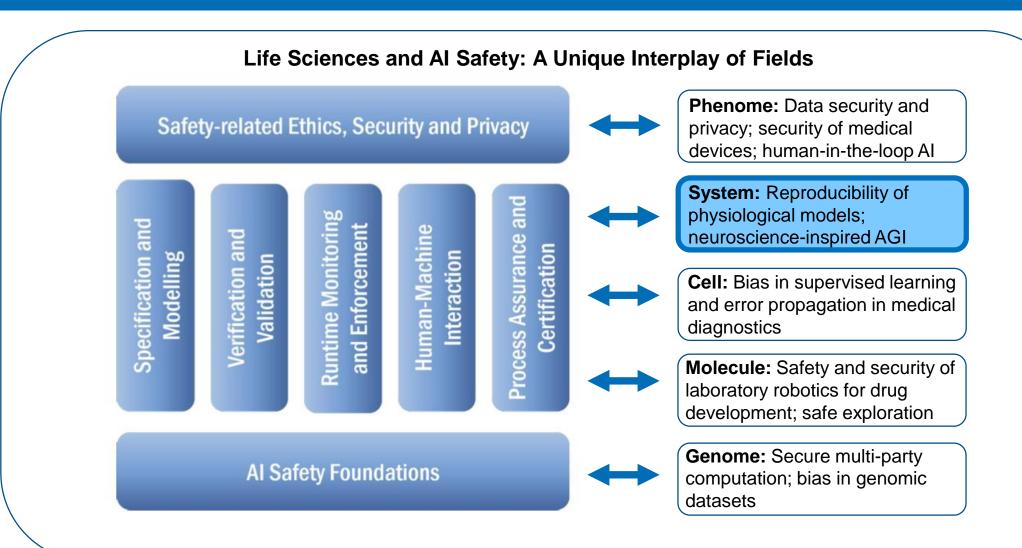
• Claim 2: Integrating AI safety and the life sciences is critical and will require significant transdisciplinary efforts



- Al will infuse genomics, cell biology, pharmaceuticals, medical devices, and care delivery
- Nearly all areas of Al safety are relevant to the life sciences
- A culture of safety is needed to address a diversity of safety challenges
- Biosecurity and biosafety are models for policy and cultural integration
  - 1975 Asilomar Conference on Recombinant DNA inspired Conference on Beneficial AI in 2017
  - Scientific community actively debating ethics of editing human genomes









G. Sarma, A. Safron, and N. Hay, "Integrative Biological Simulation, Neuropsychology, and Al Safety." *AAAI Workshop on Al Safety* (2019)

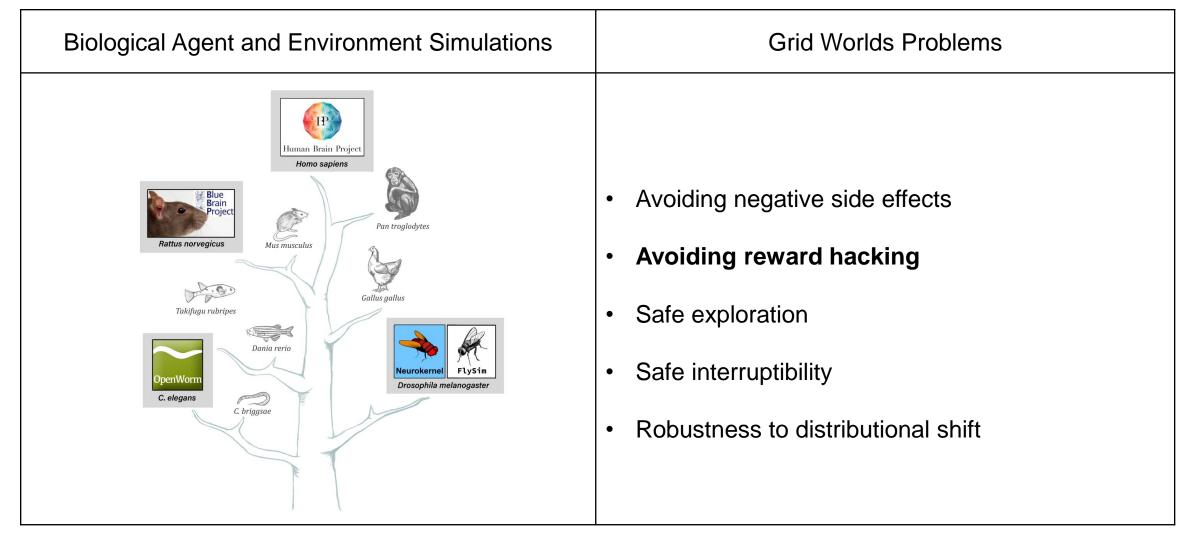
J. Leike, et al. "Al Safety Gridworlds." *arXiv preprint arXiv:1711.09883* (2017).

Biological Agent and Environment Simulations	Grid Worlds Problems
Human Brain Project  Homo sapiens  Pan troglodytes  Rattus norvegicus  Danta rerio  DentWorm  C. elegans  C. briggsae	<ul> <li>Avoiding negative side effects</li> <li>Avoiding reward hacking</li> <li>Safe exploration</li> <li>Safe interruptibility</li> <li>Robustness to distributional shift</li> </ul>



G. Sarma, A. Safron, and N. Hay, "Integrative Biological Simulation, Neuropsychology, and Al Safety." *AAAI Workshop on Al Safety* (2019)

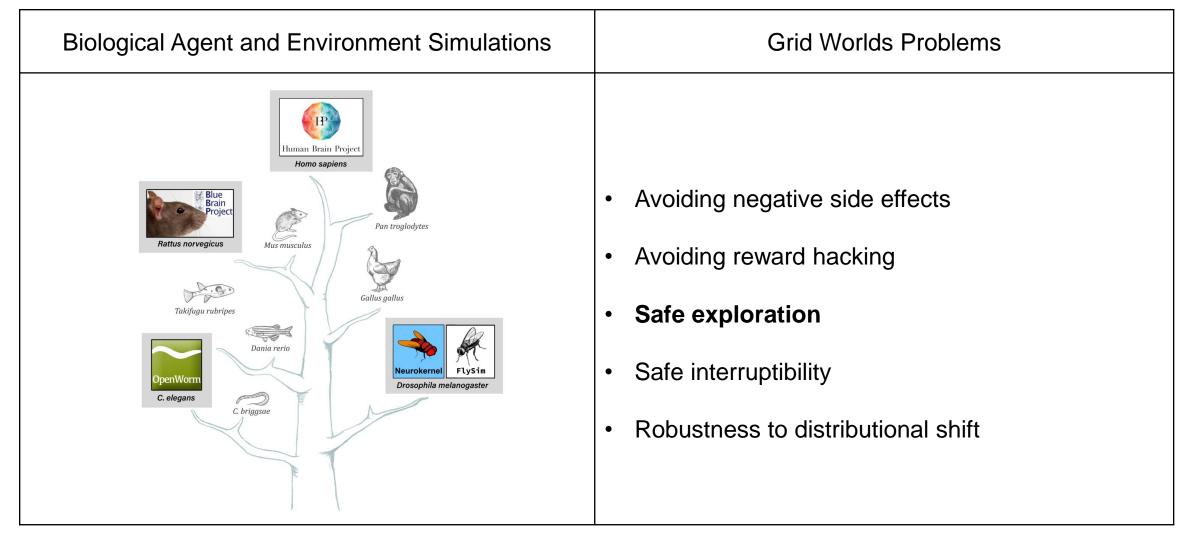
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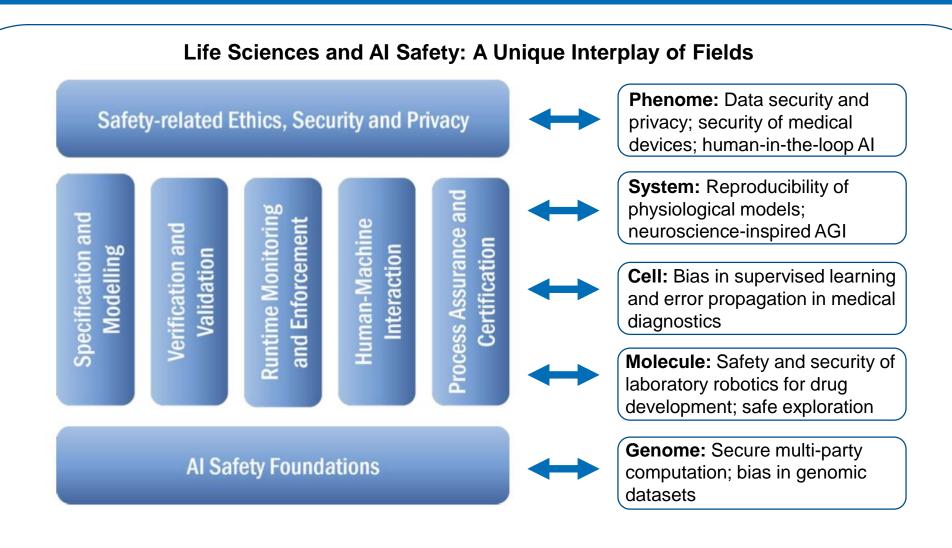
## Summary

• Claim 1: Bio-inspired AI: life sciences will advance AI itself

• Claim 2: Bio-inspired AI safety: the life sciences will advance AI safety itself



## Summary



## https://broadinstitute.org/mia

