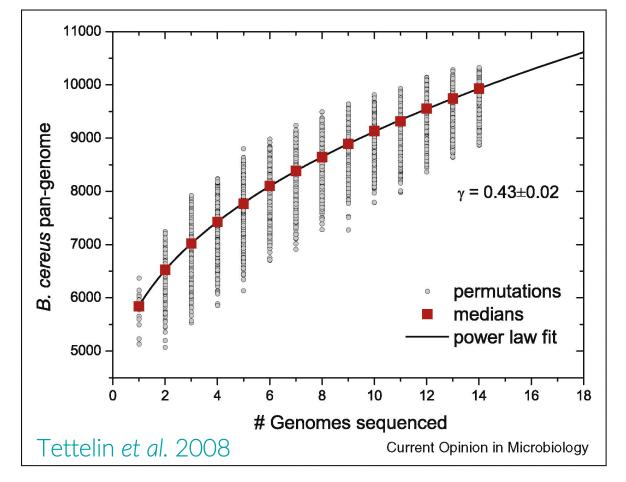
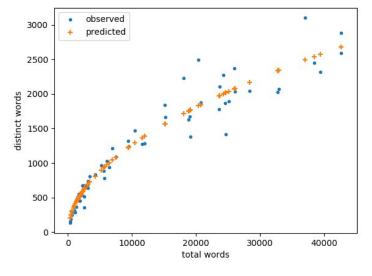
What genomics can learn from Natural Language Processing? Guillaume GAUTREAU, MaIAGE unit, StatInfOmics team 13th of June, Iabioscripting



> Pangenomics inspired by linguistic

The pangenomic concept to measure genomic diversity and stability (core and accessory genomes)





Harold Heaps (1922-2016) The Bible, King James Version, Complete

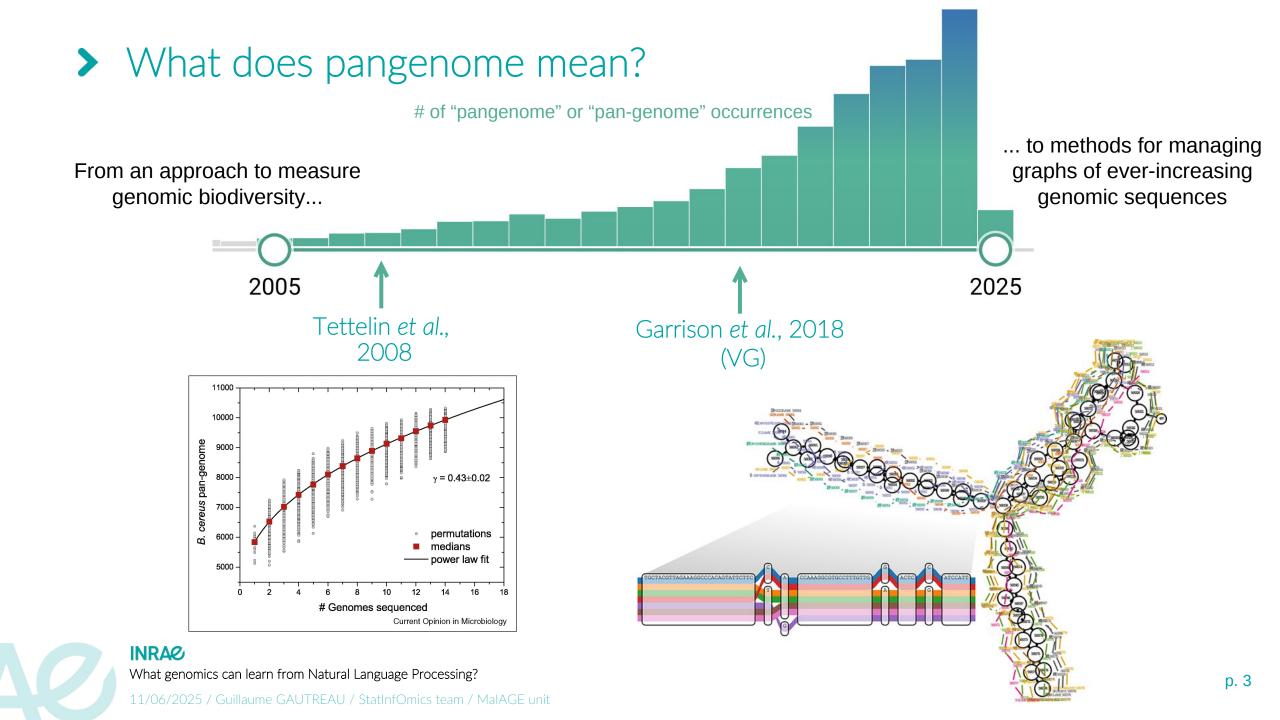
Heaps' Law is an empirical law that describes the number of distinct words in a document as an increasing function of the document length.

$$F = p(N) = \kappa N^{\gamma}$$

 $\gamma > 1$: supralinear tendancy $\gamma = 1$: linear tendancy $0 < \gamma < 1$: sublinear tendancy

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What genomics can learn from Natural Language Processing?



> Methods to handle ever-increasing genomic sequences

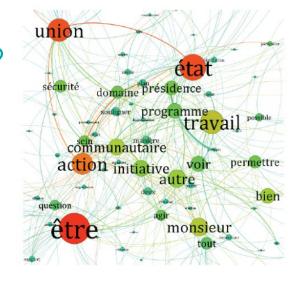
Pangenomics now deeply relies on pangenome graphs:

- pangenome graphs tries to compile all the possible (or at lest as much as possible) genomic variations sampled in a population in a graph (DBG, variation graphs..).
- But each day, genomic information became and more abundant, so these graphs grew tremendously complex !

==> Efforts to optimize these graphs and make them computationally manageable open up a significant area of research

> What to learn from Natural Language Processing ?

- Instead of building graphs of all combinations of words in sentences, research in linguistics, especially Natural Language Processing (NLP) now relies on Large Language Models (LLMs) to capture the relationships between words (more generally lexical tokens) in the language
- These models, composed of billions of parameters, are pretrained on vast datasets and can capture complex linguistic structures and semantics without explicitly mapping out all possible combinations.
- Then, these models are fine-tuned (Brown et al., 2020) to a wide range of downstream tasks (e.g.: chat bots)



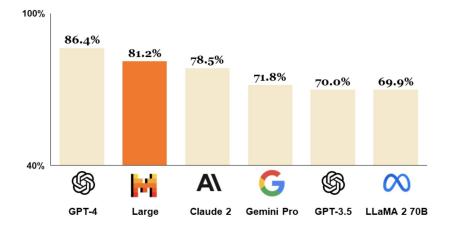


Figure 1: Comparison of GPT-4, Mistral Large (pre-trained), Claude 2, Gemini Pro 1.0, GPT 3.5 and LLaMA 2 70B on MMLU (Measuring massive multitask language understanding).

> Pangenome and Al

- It is uncertain whether constructing increasingly larger pangenome graphs using sophisticated data structures and algorithms is the best approach to deciphering and understanding biology
- Instead, due to the open-ended nature of genetic diversity (much like language ?)constructing
 pangenomes as large foundational models could help to model and capture unknown genomic
 relationships until now.

In other words, is pangenome the concept of a Foundation Model?



IA and Large Language Models Back to the basics

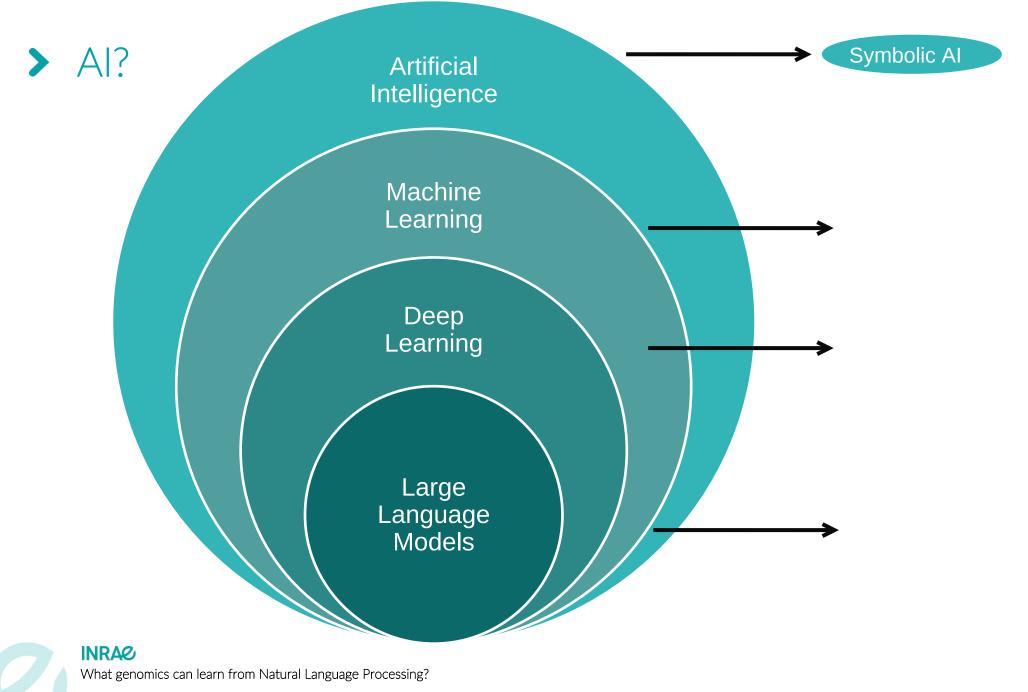
> AI legal definition (AI act)

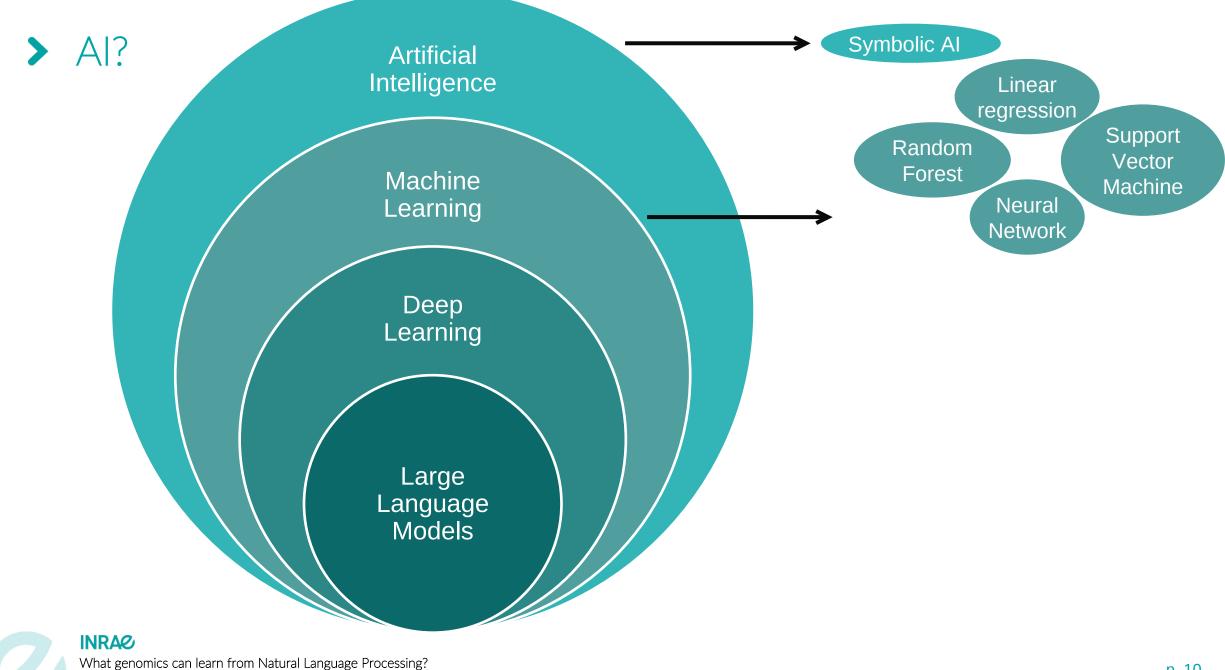
Article 3

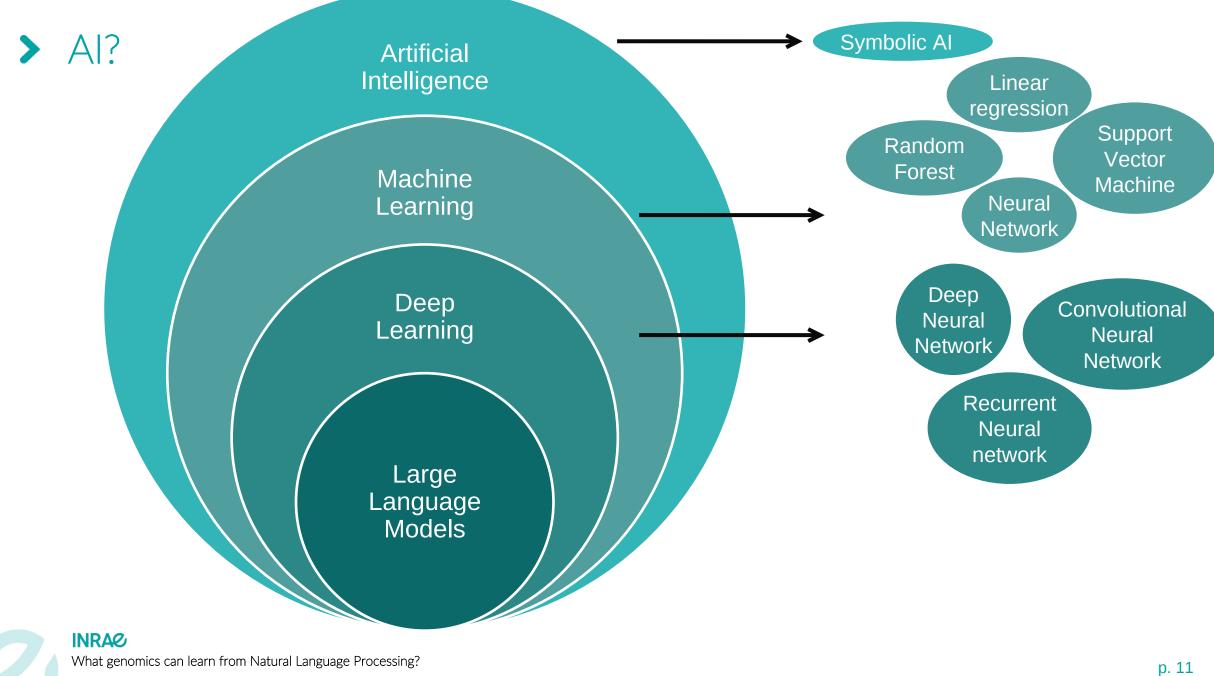
Definitions

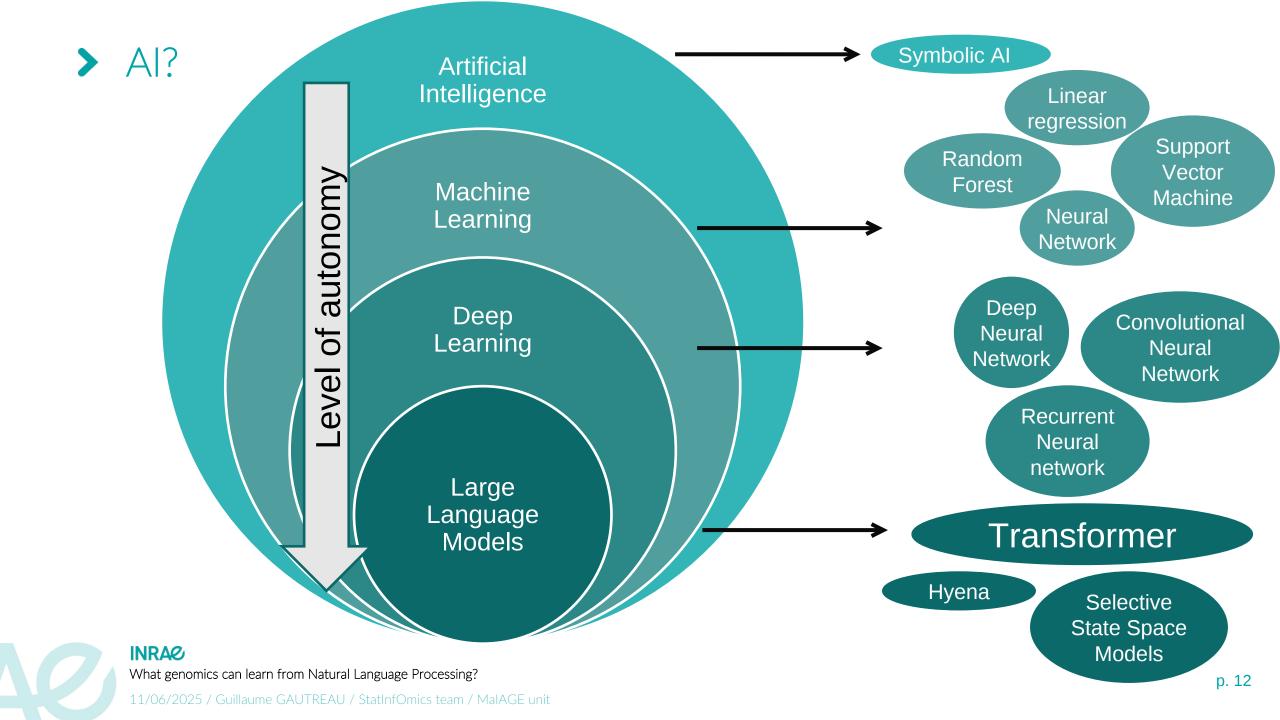
For the purposes of this Regulation, the following definitions apply:

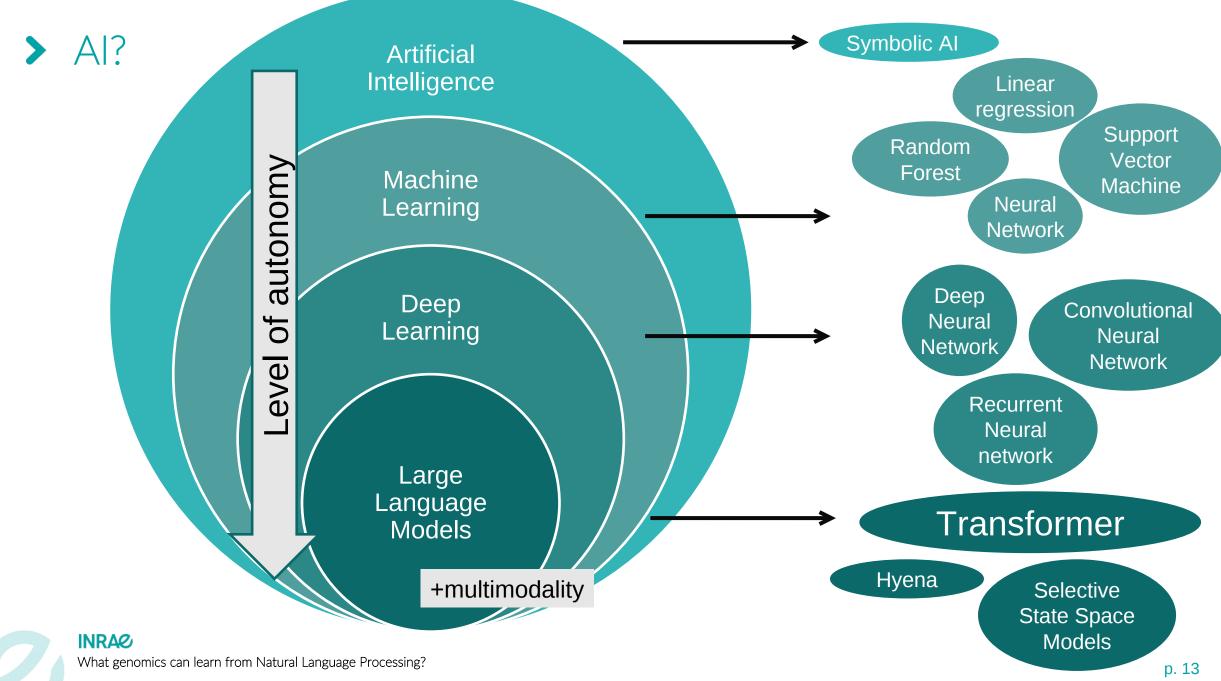
(1) 'AI system' means a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments;

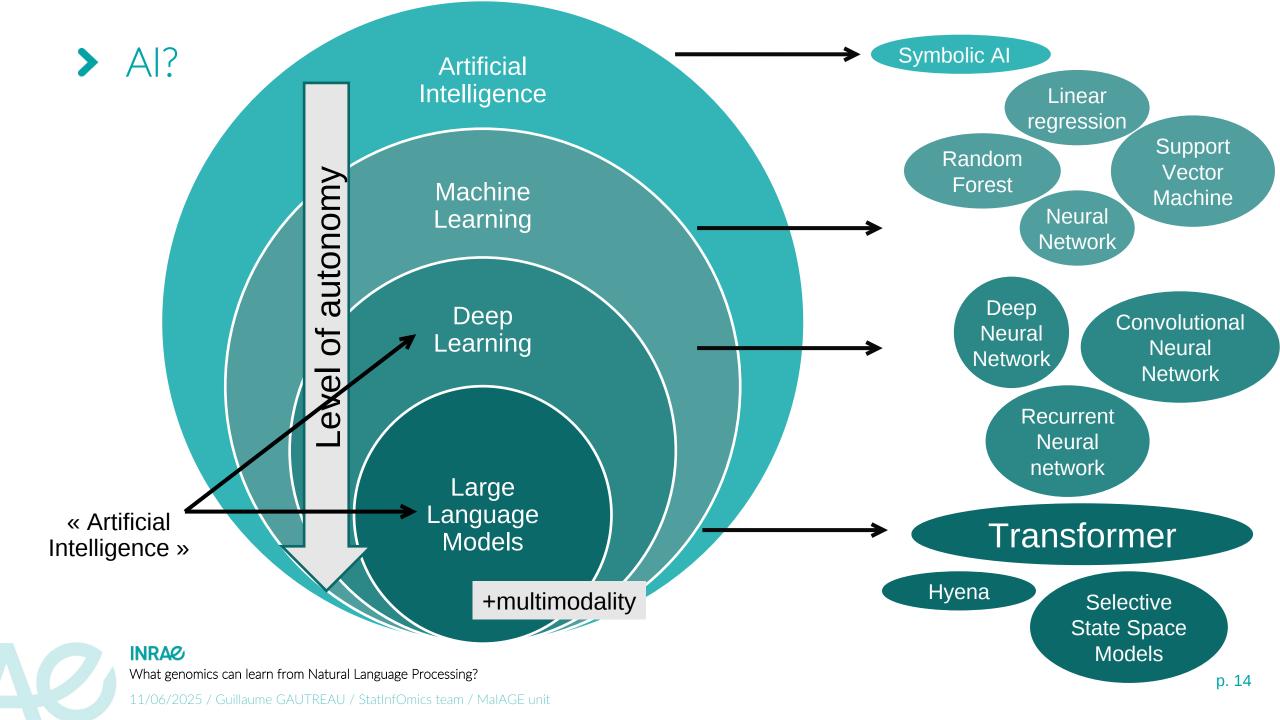












Transformer Architecture « Attention Is All You Need »

Attention Is All You Need

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Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 Englishto-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

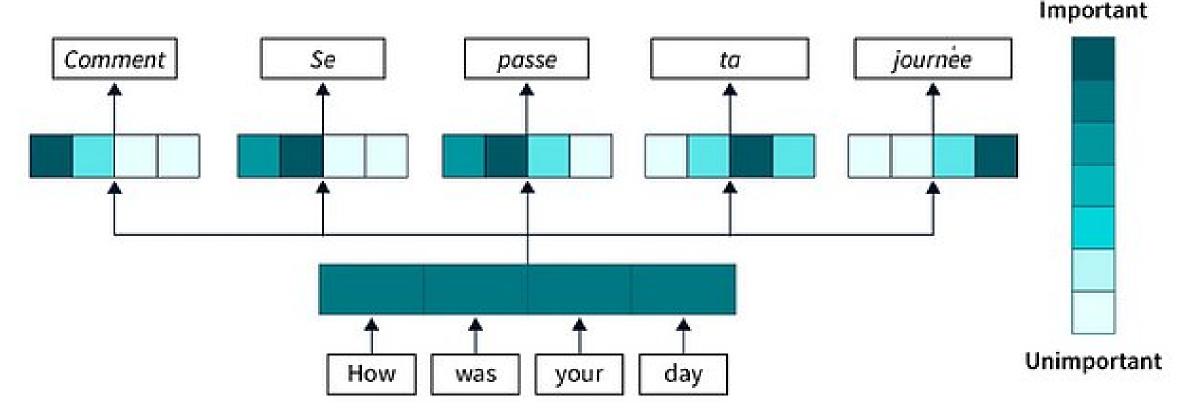
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What genomics can learn from Natural Language Processing?

- 2017 and already on track to become one of the most cited articles (>180k)
- Design for translation purposes

> The intuition of attention: look at everything, but not equally

Instead of translating word-by-word, attention looks at which English words are important for each French word



Attention finds what is most important in context to understand the actual meaning of each token

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What genomics can learn from Natural Language Processing?

11/06/2025 / Guillaume GAUTREAU / StatInfOmics team / MaIAGE unit

Tathagata, 2023p. 16https://iamtatha.medium.com/unveiling-the-power-of-attention-mechanism-revolutionizing-
artificial-intelligence-17aa209ce714p. 16

Attention Is All You Need »

Given a prompt:

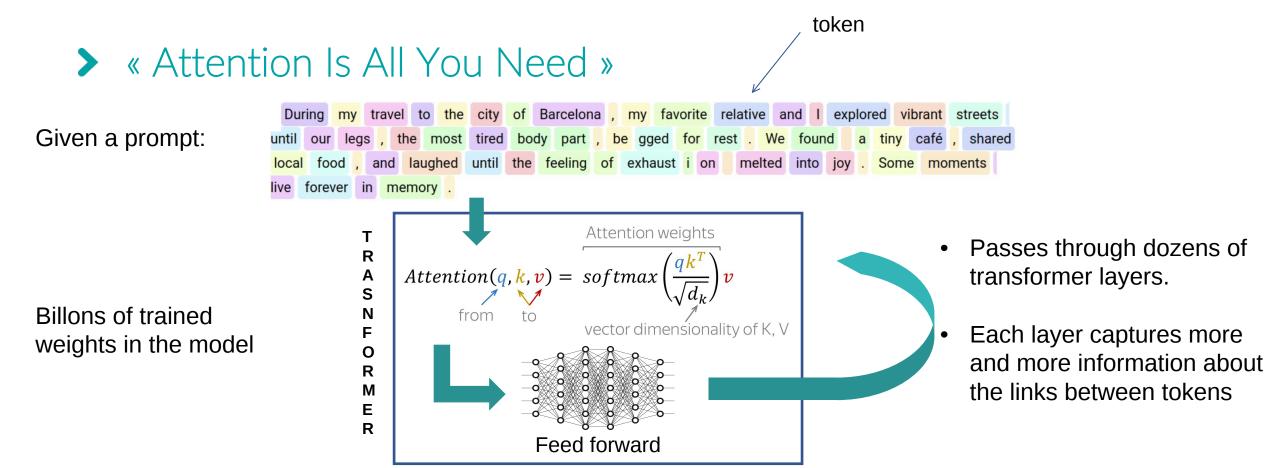
DuringmytraveltothecityofBarcelona,myfavoriterelativeandIexploredvibrantstreetsuntilourlegs,themosttiredbodypart,beggedforrest.Wefoundatinycafé,sharedlocalfood,andlaugheduntilthefeelingofexhaustionmeltedintojoy.Somemomentsliveforeverinmemory............

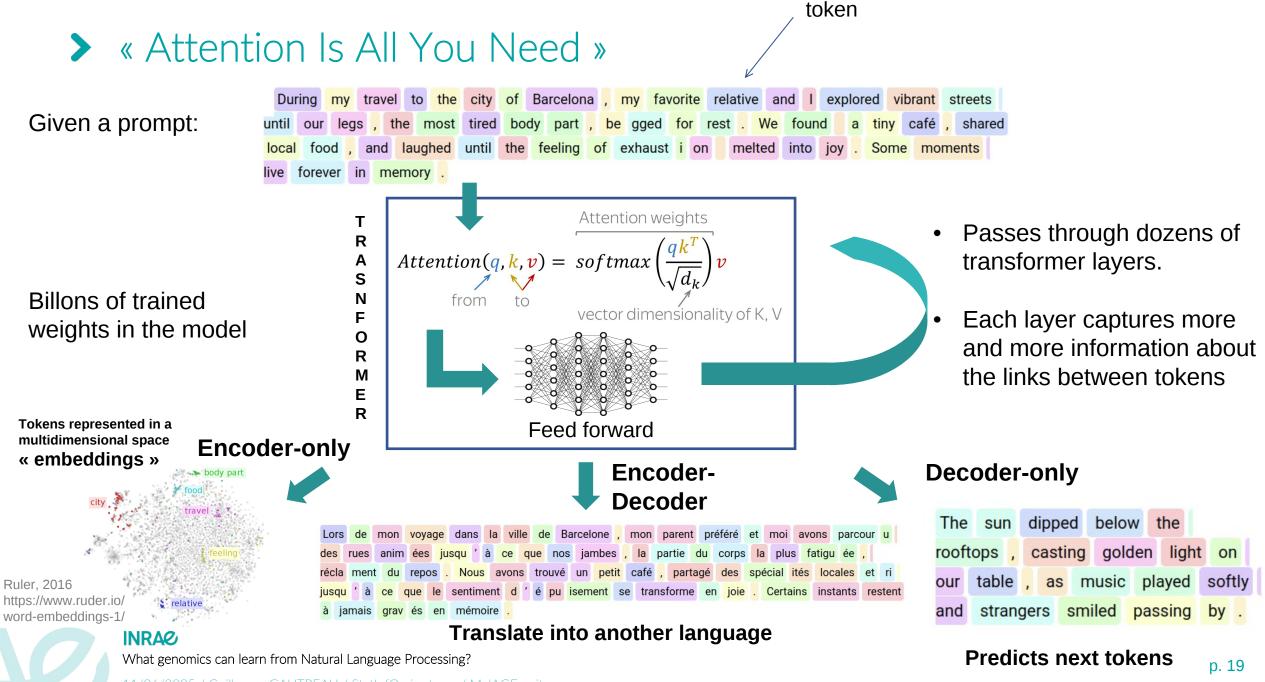
token

Ruler, 2016 https://www.ruder.io/ word-embeddings-1/

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What genomics can learn from Natural Language Processing?





INRAØ What genomics can learn from Natural Language Processing?

1. Pre-training



INRA© What genomics can learn from Natural Language Processing?

1. Pre-training



2. Evaluation / refinement / specialisation

Expert guidance highly required

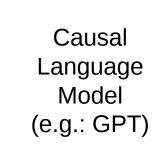


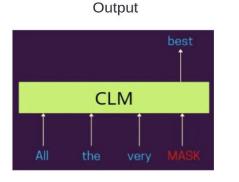
INRAØ What genomics can learn from Natural Language Processing?

Two self-supervised learning strategies:

1. Pre-training







Input: >Unidirectfomae(leftd>stight) Very MLM All the MASK best

Input

Bidirectional

Output

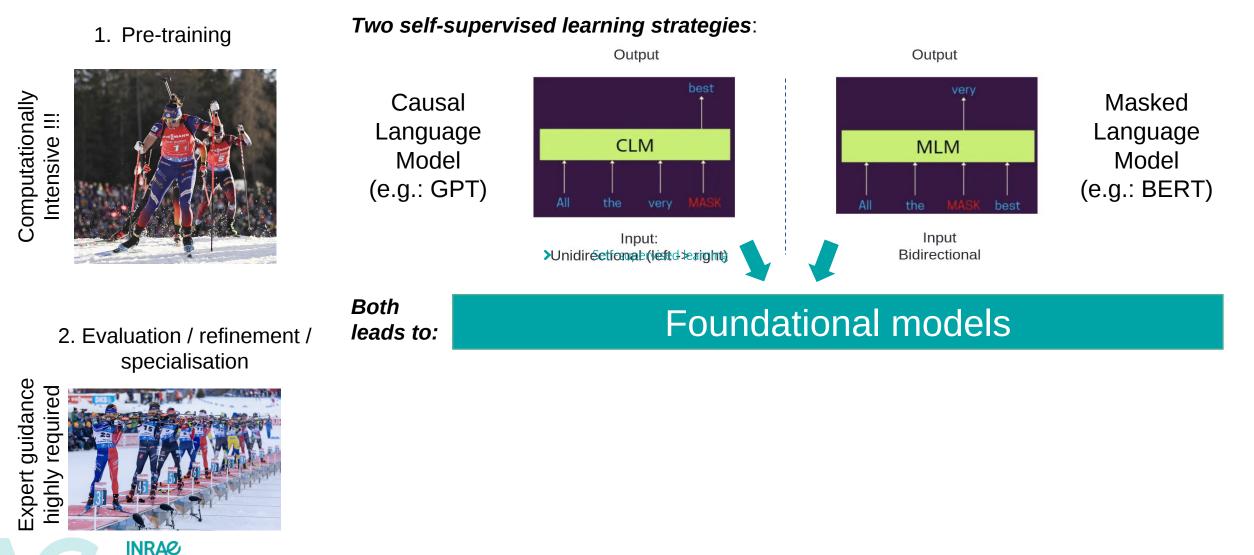
Masked Language Model (e.g.: BERT)

2. Evaluation / refinement / specialisation

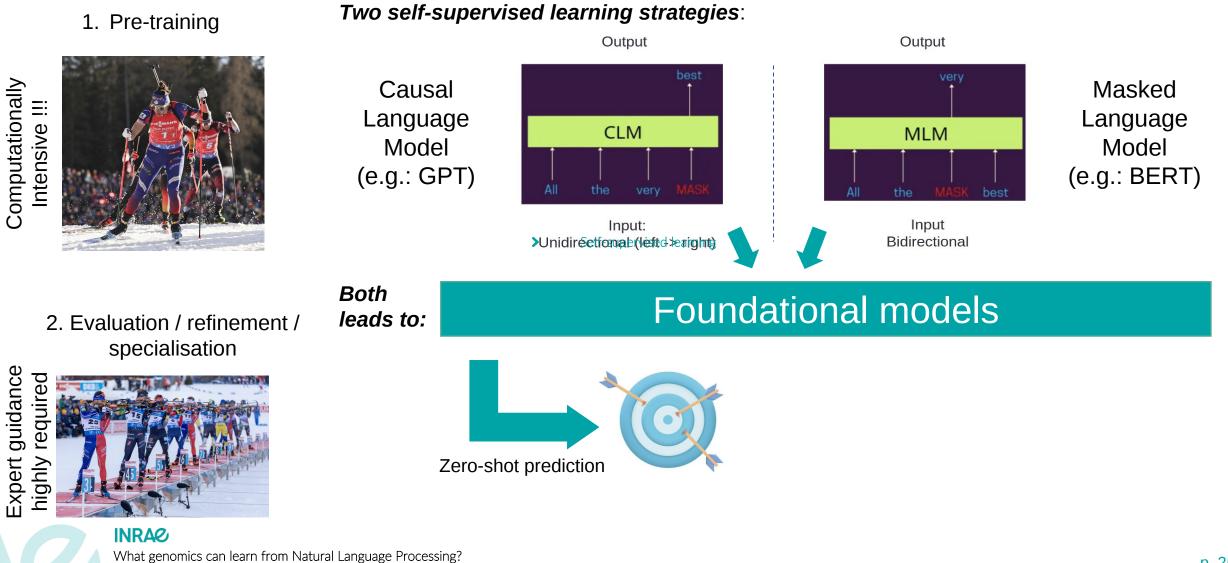
Expert guidance highly required

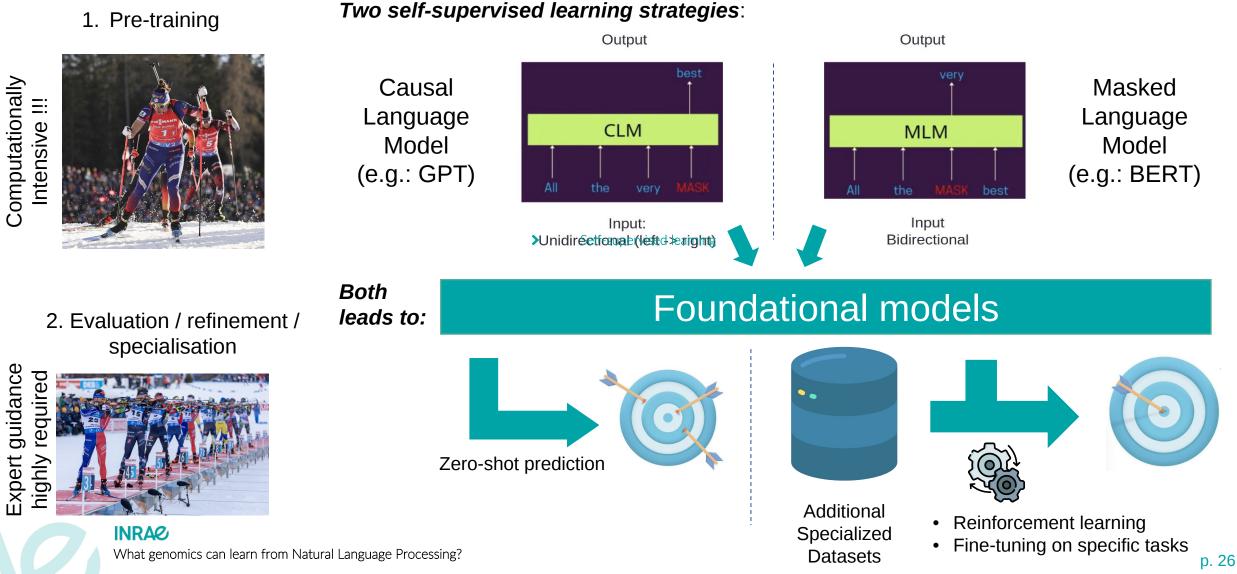


INRAØ What genomics can learn from Natural Language Processing?



What genomics can learn from Natural Language Processing?



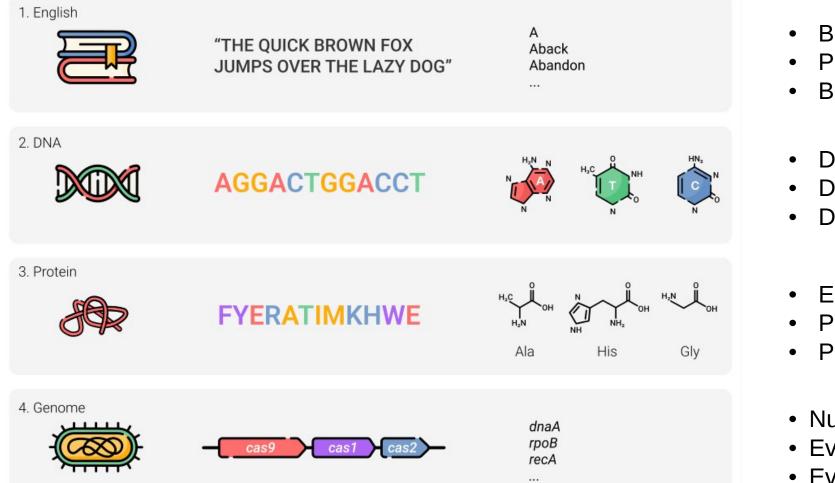




From NLP to genomic: Evo 2

Towards generalistic Large Language of Life Models (LLLM)

Large Language of Life Models (LLLM)



- BioMedLM
- PubMedBERT
- BioBERT
- DNABERT
- **DNABERT-2**
- **DNABERT-S**
- ESM
- ProteinBERT
- ProtMamba
- Nucleotide Transformer
- Evo
- Evo2

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What genomics can learn from Natural Language Processing?

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Rannon et al. 2025

https://doi.org/10.48550/arXiv.2506.02212

> Evo (november 2024)

RESEARCH ARTICLE

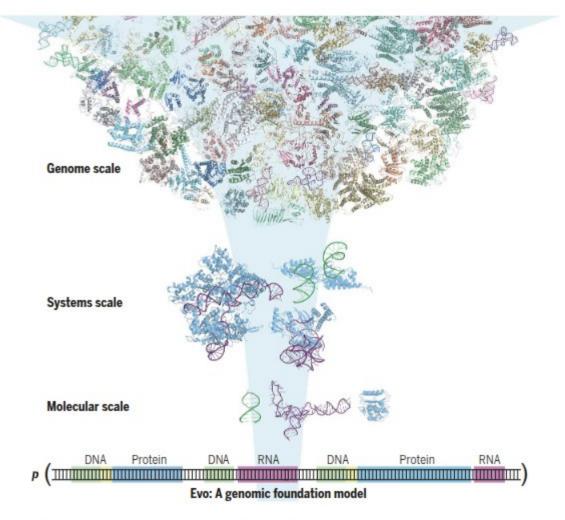
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GENERATIVE GENOMICS

Sequence modeling and design from molecular to genome scale with Evo

Eric Nguyen^{1,2}⁺, Michael Poli^{3,4}⁺[‡], Matthew G. Durrant¹⁺, Brian Kang^{1,2}⁺, Dhruva Katrekar¹⁺, David B. Li^{1,2}⁺, Liam J. Bartie¹, Armin W. Thomas⁵, Samuel H. King^{1,2}, Garyk Brixi^{1,6}, Jeremy Sullivan¹, Madelena Y. Ng⁷, Ashley Lewis⁸, Aaron Lou³, Stefano Ermon^{3,9}, Stephen A. Baccus¹⁰, Tina Hernandez-Boussard⁸, Christopher Ré³, Patrick D. Hsu^{1,11*}, Brian L. Hie^{1,5,12*}

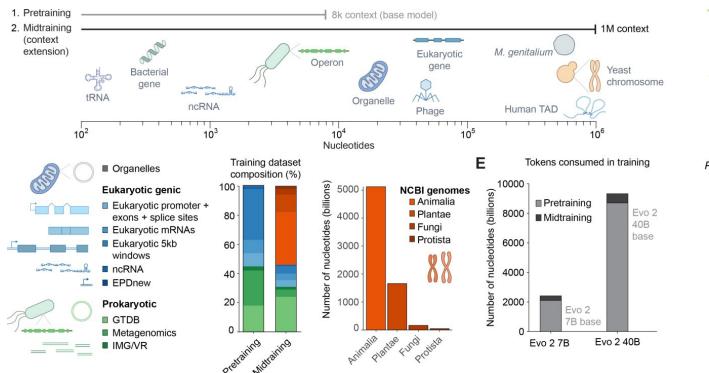
The genome is a sequence that encodes the DNA, RNA, and proteins that orchestrate an organism's function. We present Evo, a long-context genomic foundation model with a frontier architecture trained on millions of prokaryotic and phage genomes, and report scaling laws on DNA to complement observations in language and vision. Evo generalizes across DNA, RNA, and proteins, enabling zero-shot function prediction competitive with domain-specific language models and the generation of functional CRISPR-Cas and transposon systems, representing the first examples of protein-RNA and protein-DNA codesign with a language model. Evo also learns how small mutations affect whole-organism fitness and generates megabase-scale sequences with plausible genomic architecture. These prediction and generation capabilities span molecular to genomic scales of complexity, advancing our understanding and control of biology.

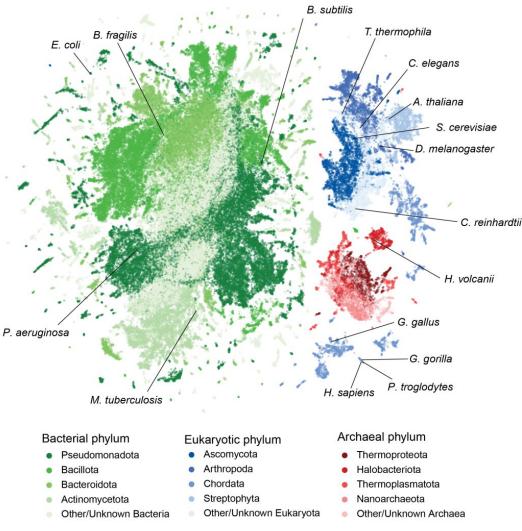


Evo, a 7-billion-parameter genomic foundation model, learns biological complexity from individual nucleotides to whole genomes. Trained on 2.7 million raw prokaryotic and phage genome sequences, Evo is naturally multimodal, enabling the codesign of DNA, RNA, and protein molecules that form higher-order functional systems. Evo is also inherently multiscale, enabling prediction and generation tasks at the level of molecules, systems, and genomes.

> Evo2 (preprint released in february)

- Built to predict the next token (GPT-like architecture).
- Single-nucleotide resolution
- Uses a different architecture than Transformers to handle genome-scale context efficiently (Hyena, optimized sub-quadratic architecture)
- Training cost ~5-10 M\$ (GPU + electricity only)
- Developed in direct collaboration with NVIDIA to manage computation

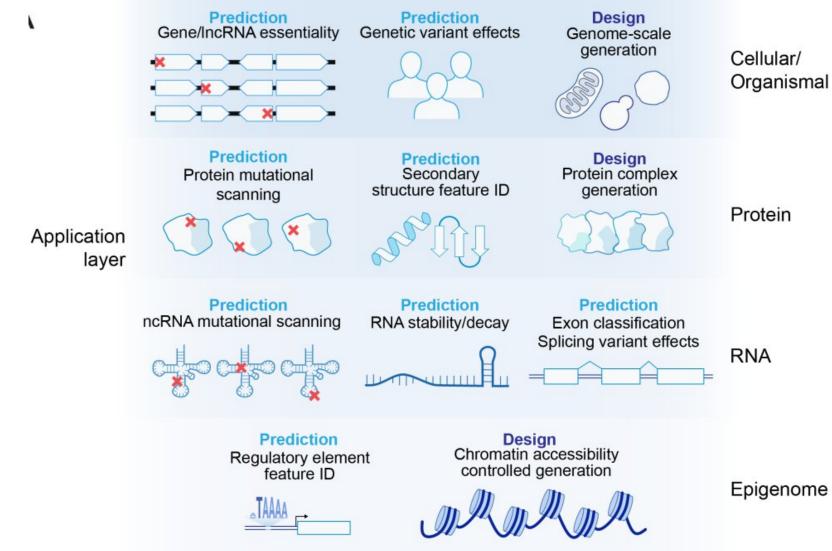




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What genomics can learn from Natural Language Processing?

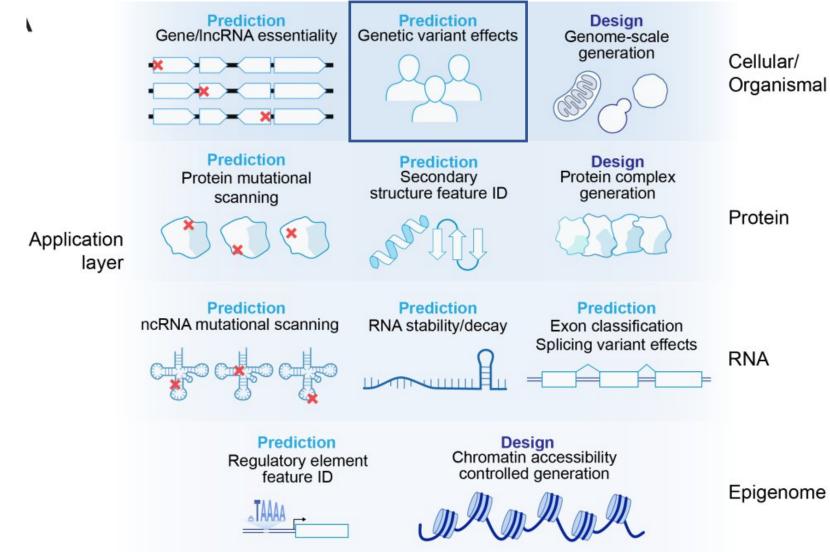
> Applications



What genomics can learn from Natural Language Processing?

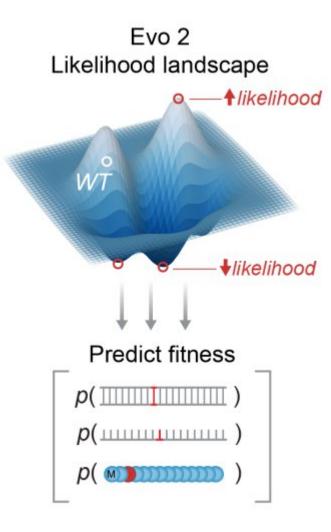
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> Applications

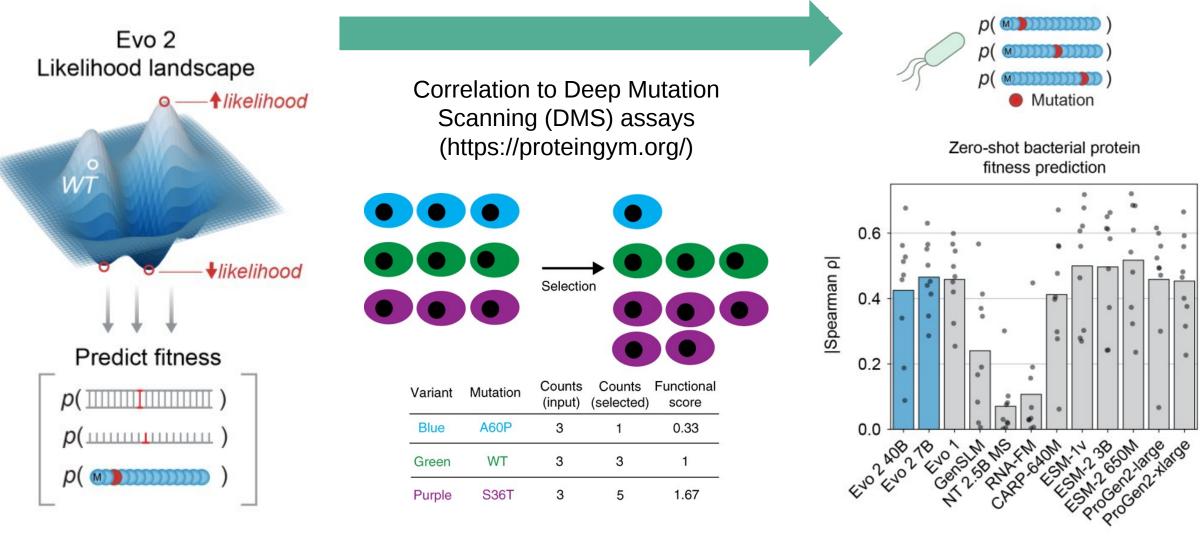


INRA What genomics can learn from Natural Language Processing?

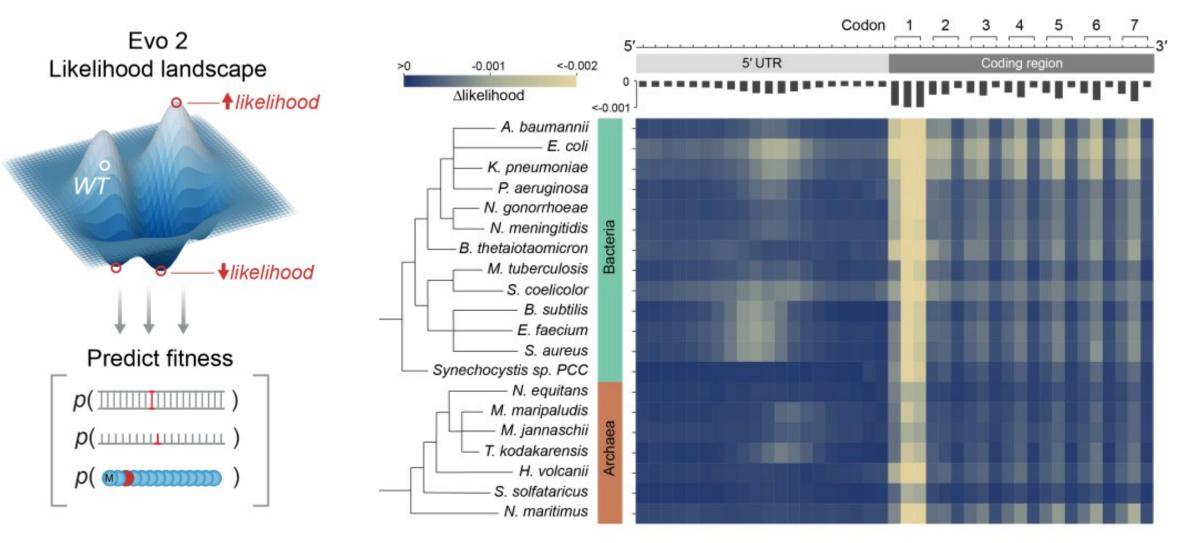
> Applications: zero-shot prediction of variant effects



> Applications: zero-shot prediction of variant effects

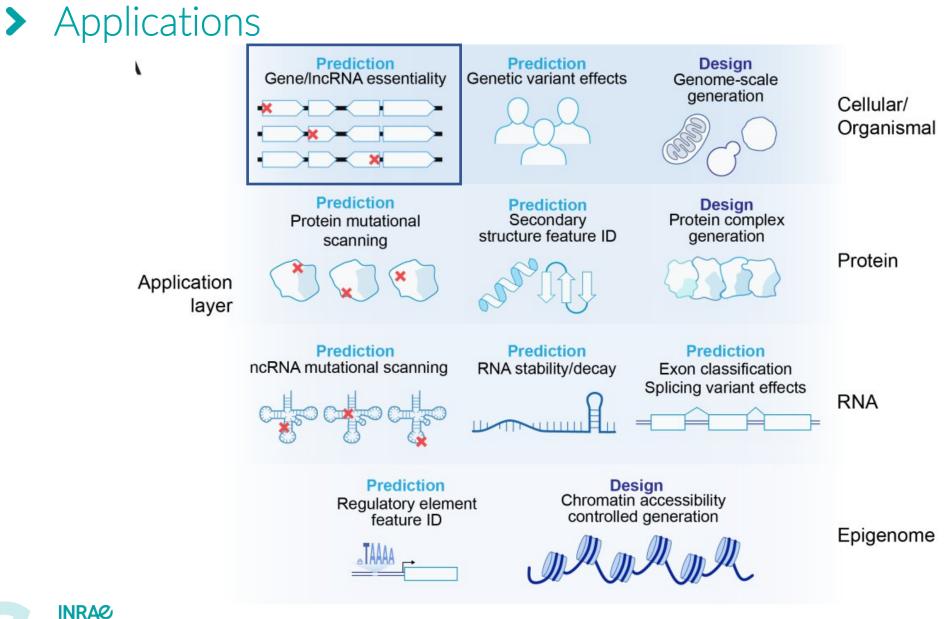


> Applications: zero-shot prediction of variant effects



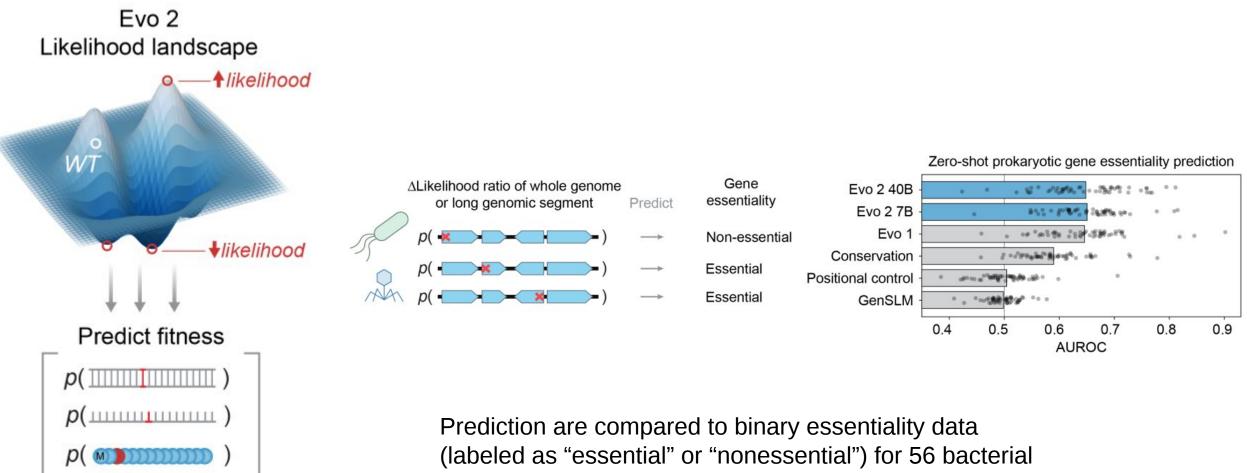
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What genomics can learn from Natural Language Processing?



What genomics can learn from Natural Language Processing?

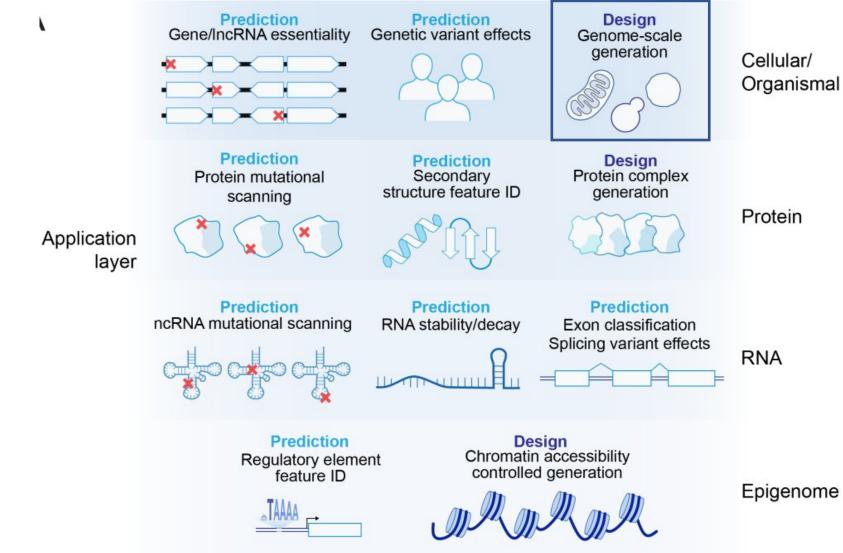
> Applications: prediction of gene essentiality



genomes from the DEG database (Zhang, 2004).

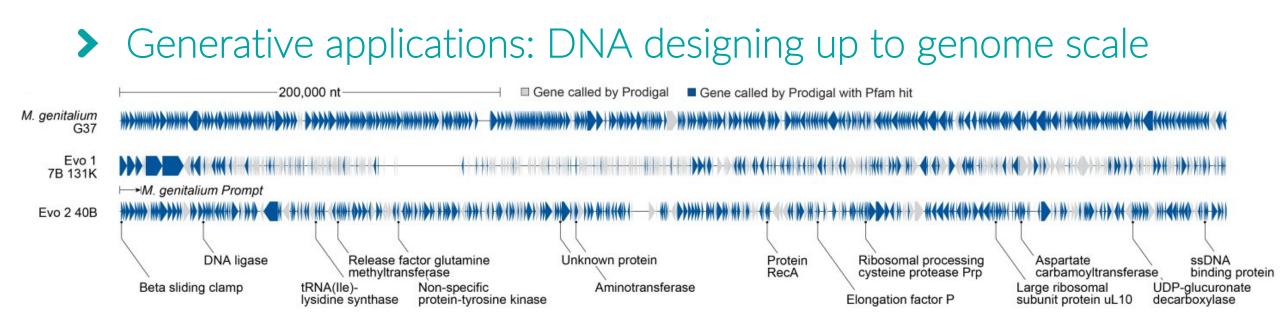
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> Applications



What genomics can learn from Natural Language Processing?

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- Synthetic design: generate proteins, enzymes, operons, pathways
- Promoter engineering: generate inducible / tunable promoters
- Anonymization: generate synthetic genomes preserving signal
- Benchmarking: generate realistic synthetic datasets, diversity normalization
- Pangenome compression: generate normalized representations
- Assembly gap filling (MAGs)
- Any other idea?

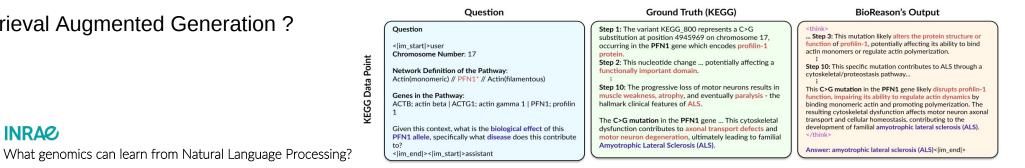
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What genomics can learn from Natural Language Processing?

Conclusion on Evo2

- Highly versatile model. Idea : reinforcement learning to generate microbial ecosystems (synthetic ecology)?
- Openly available, but requires an Nvidia H100 GPU (~30k€) to run locally
- → User-friendly interface available: <u>https://arcinstitute.org/tools/evo/evo-designer</u>
- Ethical considerations to anticipate (biosecurity, misuses)
 - Bioterrorism (human pathogenic viruses weren't included in Evo2)
 - Fake dataset pollution, science integrity issues... ٠
- Partially interpretable via Sparse AutoEncoders (explored in the Evo2 article)
- Personal opinion from our first tries (M2 intern): still a big margin of improvement (at least on Evo1)
- Next step: LLM x LLLM : « Talk to your genome »
 - ChatNT (published last week in Nature Machine Intelligence)
 - BioReason (Evo2 x Qwen3), preprint on Arxiv
- **Retrieval Augmented Generation ?**

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> Conclusion on Evo2

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Question

Ground Truth (KEGG)

Step 1: The variant KEGG_800 represents a C>G substitution at position 4945969 on chromosome 17, occurring in the PFN1 gene which encodes profilin-1 protein.
Step 2: This nucleotide change ... potentially affecting a functionally important domain.
Step 10: The progressive loss of motor neurons results in muscle weakness, atrophy, and eventually paralysis - the hallmark clinical features of ALS.
The C>G mutation in the PFN1 gene ... This cytoskeletal dysfunction contributes to axonal transport defects and motor neuron degeneration, ultimately leading to familial Amyotrophic Lateral Sclerosis (ALS).
Step 1: The variant KEGG_800 represents a C>G substitution at position 4945969 on chromosome 17, occurring in the PFN1 gene ... This cytoskeletal dysfunction contributes to axonal transport defects and motor neuron degeneration, ultimately leading to familial Amyotrophic Lateral Sclerosis (ALS).



BioReason's Output

... Step 3: This mutation likely alters the protein structure or function of profilin-1, potentially affecting its ability to bind actin monomers or regulate actin polymerization.

Step 10: This specific mutation contributes to ALS through a cytoskeletal/proteostasis pathway...

This C>G mutation in the PFN1 gene likely disrupts profilin-1 function, impairing its ability to regulate actin dynamics by binding monomeric actin and promoting polymerization. The resulting cytoskeletal dysfunction affects motor neuron axonal transport and cellular homeostasis, contributing to the development of familial amyotrophic lateral sclerosis (ALS).

Answer: amyotrophic lateral sclerosis (ALS)<|im_end|>

KEGG Data Point

Network Definition of the Pathway: Actin(monomeric) // PFN1* // Actin(filamentous) Genes in the Pathway:

ACTB; actin beta | ACTG1; actin gamma 1 | PFN1; profilin

Given this context, what is the biological effect of this PFN1 allele, specifically what disease does this contribute to? <|im_end|><|im_start|>assistant

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Question

start

Chromosome Number: 17

What genomics can learn from Natural Language Processing?