Beyond Human Language CSC2541H1 Topics in Machine Learning, Winter 2025, UToronto

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Announcements



Questions?

Today

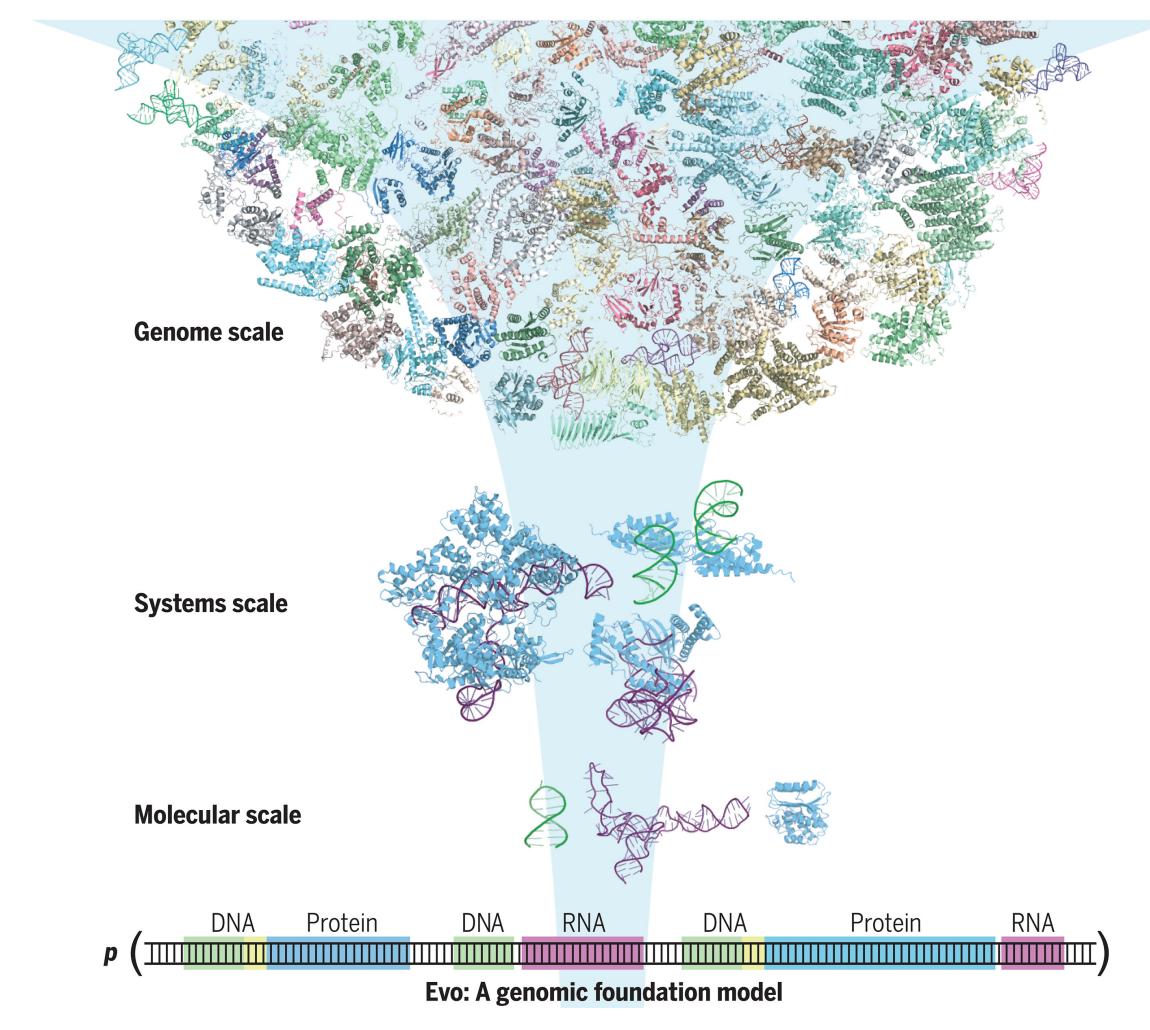
- Natural language is not the only data in the world.
 - By volume, particle colliders probably produce the largest number of bits*.
- Today's topics
 - Vision Language Models (Flamingo and JetFormer)
 - Genomic Foundation Models (Evo)
- Similar themes emerge, but there are some unique challenges.

* Clissa et al. 2023. How big is Big Data? A comprehensive survey of data production, storage, and streaming in science and industry.

Long Contexts Challenge 1

- Scale along the time axis is a serious challenge in some domains (video, genomics)
- Genomes are sequences of nucleotides that store the instructions for the synthesis of biomolecules in cells.
- Genomes have small alphabets (A, C, G, T for DNA) but are very long, up to 160B nucleotides*.

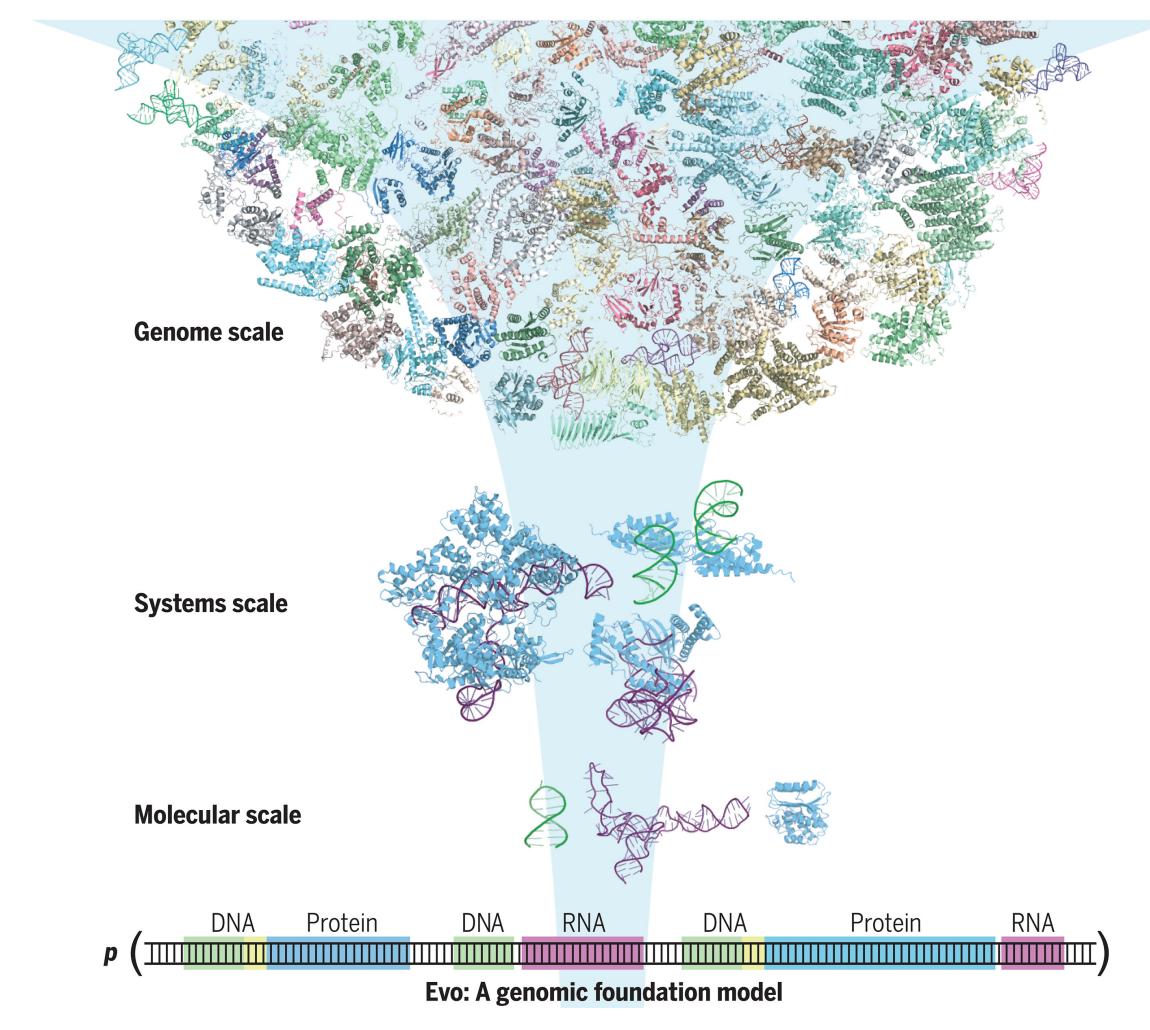
* Fernández et al. 2024. A 160 Gbp fork fern genome shatters size record for eukaryote.



Nguyen et al. 2024. Sequence modeling and design from molecular to genome scale with Evo.

Long Contexts Challenge 1

- Arguably a genome is similar to a document or a novel or a software library.
- Would love to fit a whole genome in context, but this is challenging if we model at a singlenucleotide resolution.



Nguyen et al. 2024. Sequence modeling and design from molecular to genome scale with Evo.

Multimodality Why?

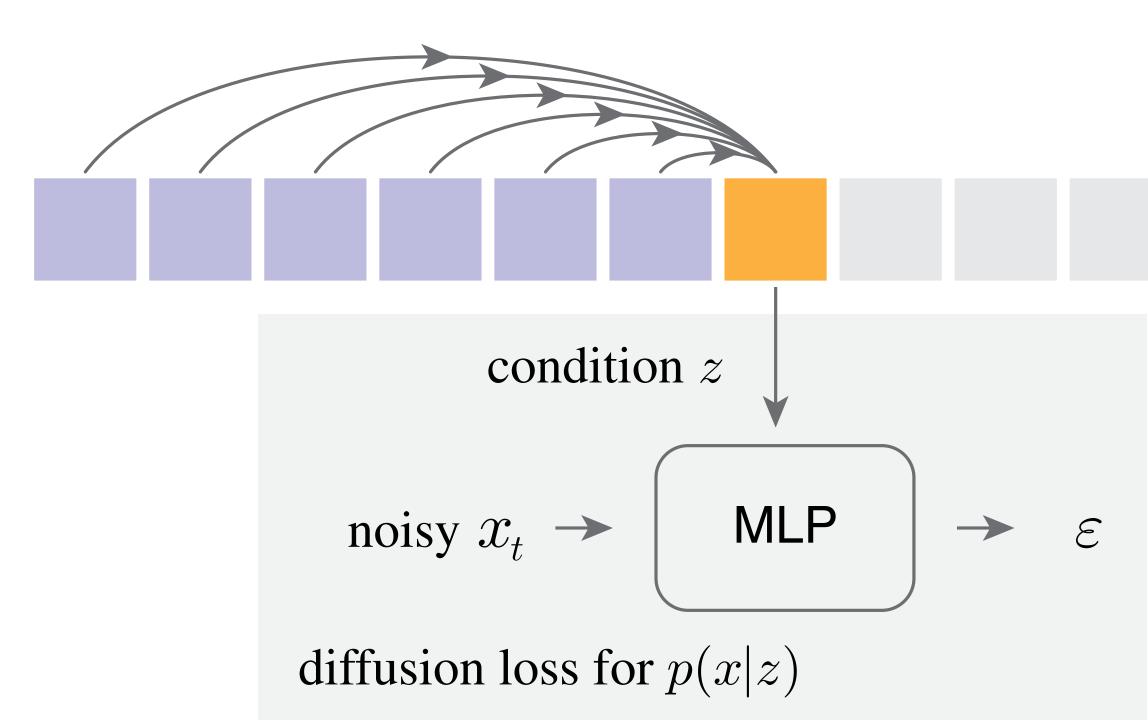
- Multimodality tends to refer to combining data types from different measurements (e.g., image and text).
- Some data is not modelled well by sequences of a finite alphabet.
 - If it has geometric structure, e.g., weather on the surface of the earth, that we want to model.
- Humans prefer to communicate multi-modally.
 - Even if it's inefficient from an information theoretic perspective, we sometimes prefer to communicate visually.

Transfer between Modalities: Fixes: = model compresse Suppose we directly model p(text, pixels, sound) + compose auto with a power with one big autoregressive transformer. Pros: · image generation augments inowledge · next level text renderiv · native in-context lear · unified post-training Cons: · varying bit-rate d · compute not ada okens -> tran

Synthetic image from GPT 40 native image generation release.



- Ideally: a large model trained on the joint over all data types.
- Possible in principle:
 - Transformers produce embeddings of sequences to parameterize a distribution over a finite alphabet.
 - We can use the next token embedding to parameterize a distribution over any space.



Tianhong et al, 2024, Autoregressive Image Generation without Vector Quantization

- Key challenge: loss magnitudes can vary wildly across modalities.
- One way to think about this is to think about compression.
- The more information contained in a modality, generally the more it will dominate the loss.

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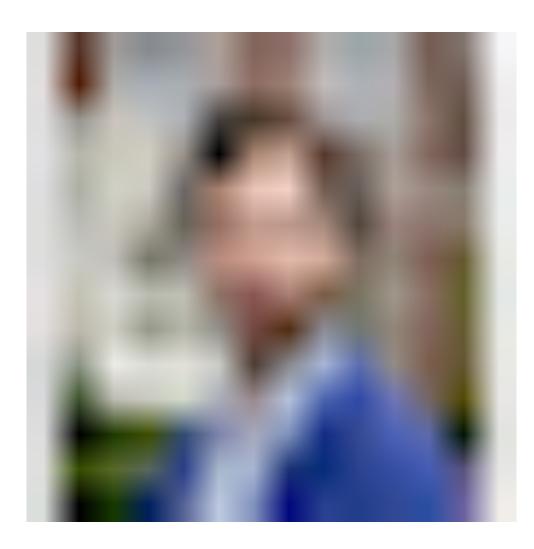
Synthetic image from GPT 40 native image generation release.



- How much information is in different modalities?
- Finite alphabets: at most log2(N) bits to store where N is the size of the alphabet.
- Real-value alphabets: You cannot store a real number with infinite precision any any number of bits.
- This is why we have lossy compressors like JPEG for images.

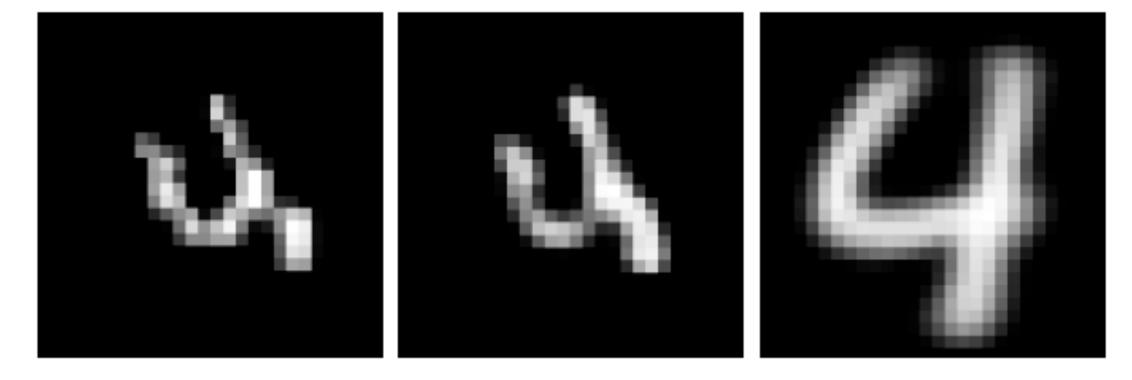


High bitrate



Low bitrate

- Lossy compressors have to decide what to model.
 - Ideally we model "what matters to humans"
 - But this is not well-specified.
- In other words, what we choose to model in the loss is not wellspecified and has an impact on the bitrate of that modality.



Source Standard rec. Our rec.

- Varying bitrate between modalities can hurt model training because sources with very high bitrate are overweighted in the loss.
- Take-home: high bitrate modalities dominate naive training losses like cross-entropy but do not reflect what humans necessarily care about.

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