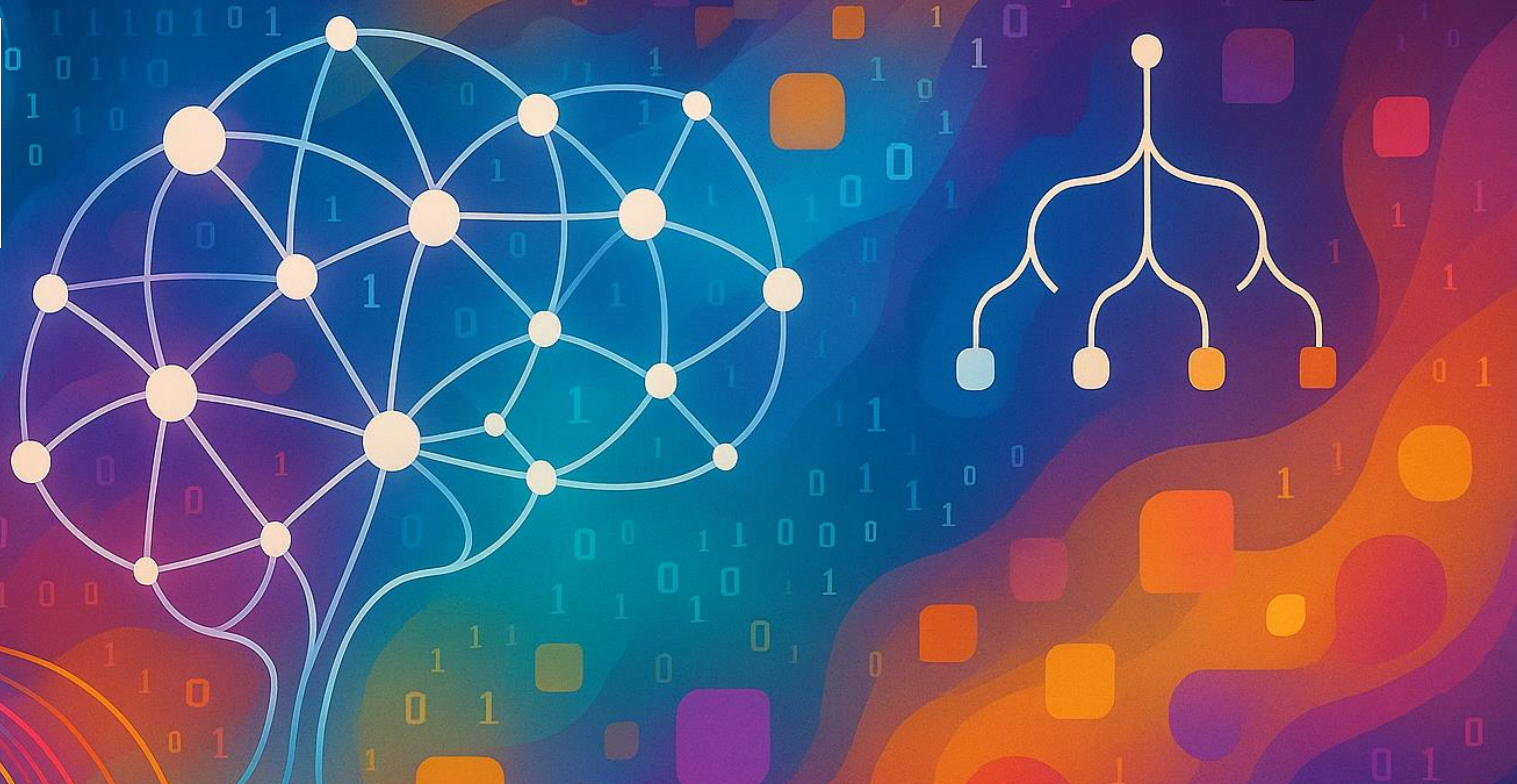


Tutorial on Language Generation

Organizers: *Moses Charikar, Anay Mehrotra, Charlotte Peale, Chirag Pabbaraju, Grigoris Velegkas*

Diverse and Robust Generation

Charlotte Peale
Stanford University

COLT Tutorial on Language Generation – June 30, 2025

This Talk:

Two Extensions of the Language Generation Model

1. Generating with **diversity** constraints

   Representative Language Generation, [CP, Vinod Raman, Omer Reingold]

2. Generating from **noisy data**

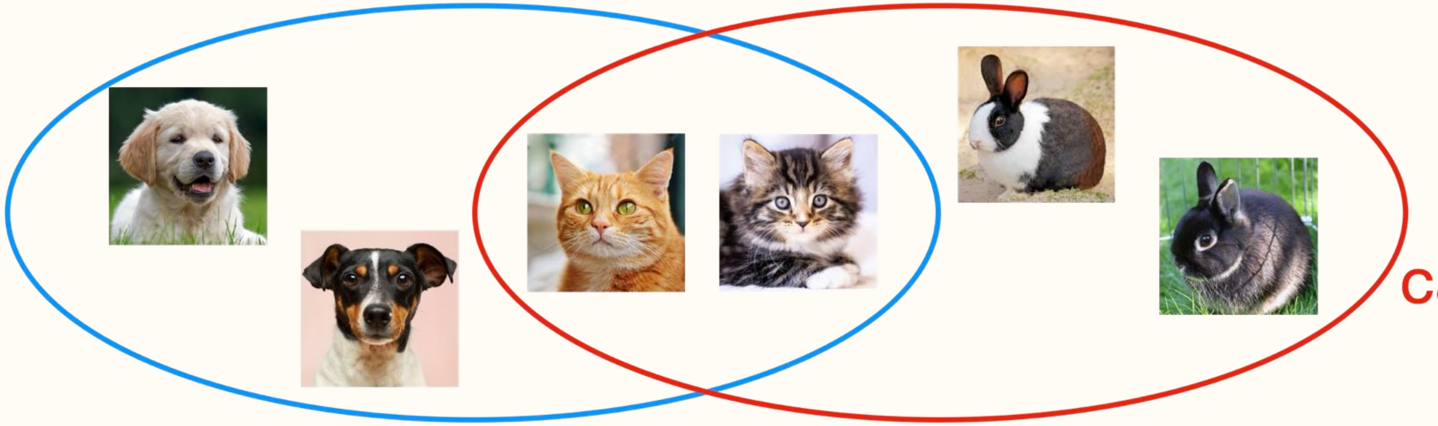
   Generation from Noisy Examples, [Ananth Raman, Vinod Raman]

Representative Generation

CP, Vinod Raman, Omer Reingold (ICML, 2025)

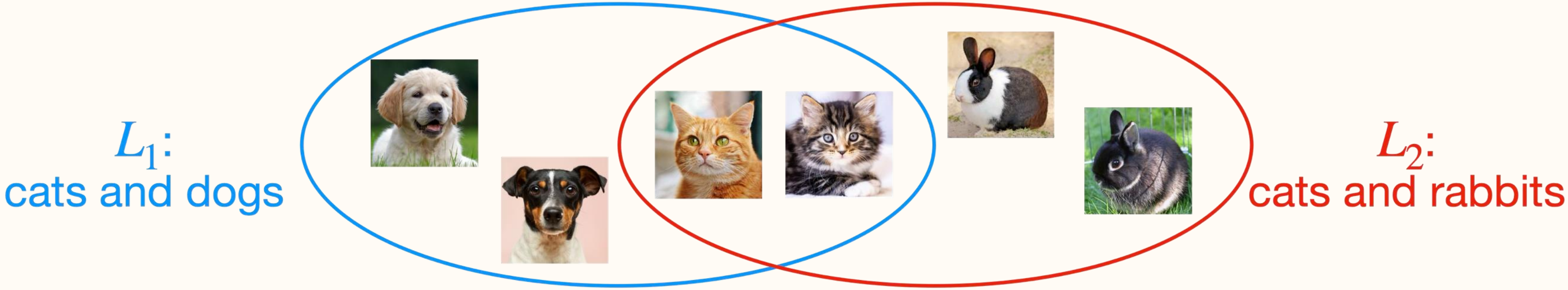
Revisiting Breadth

L_1:
cats and dogs



L_2:
cats and rabbits

Revisiting Breadth



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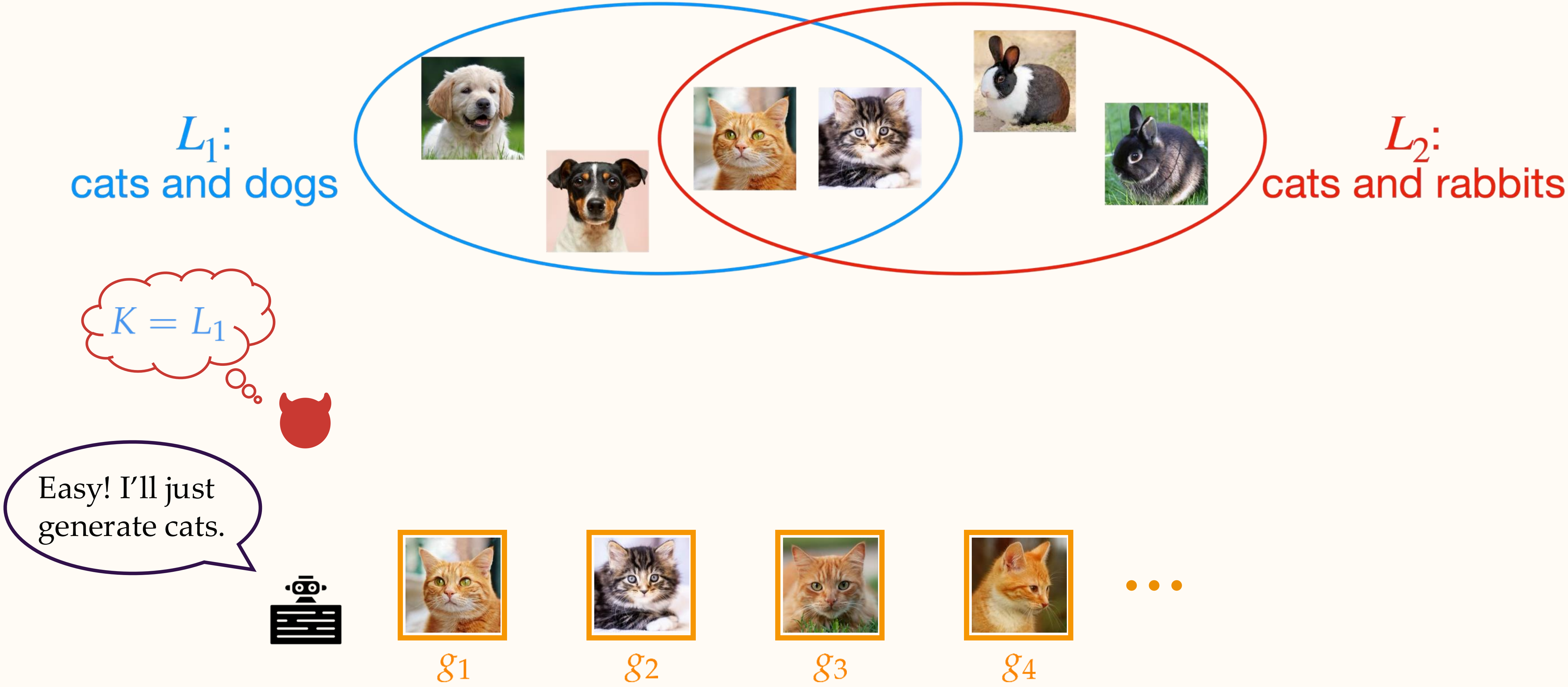

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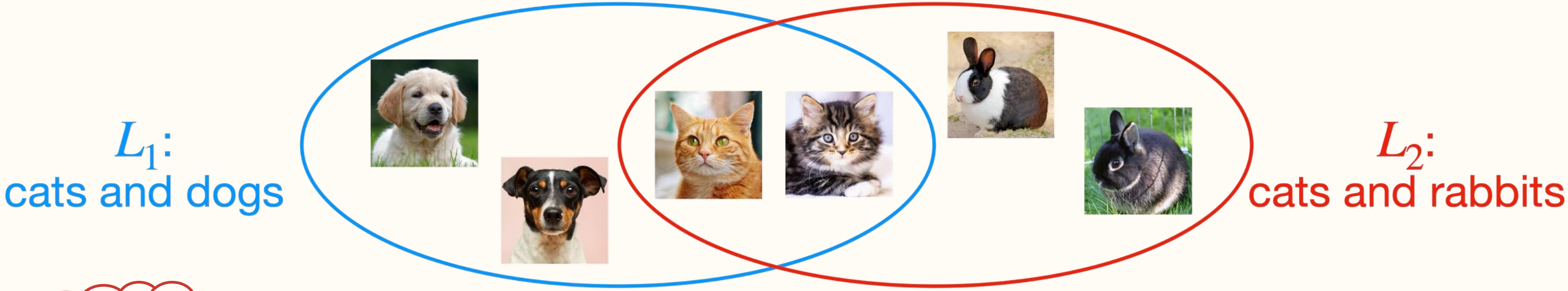

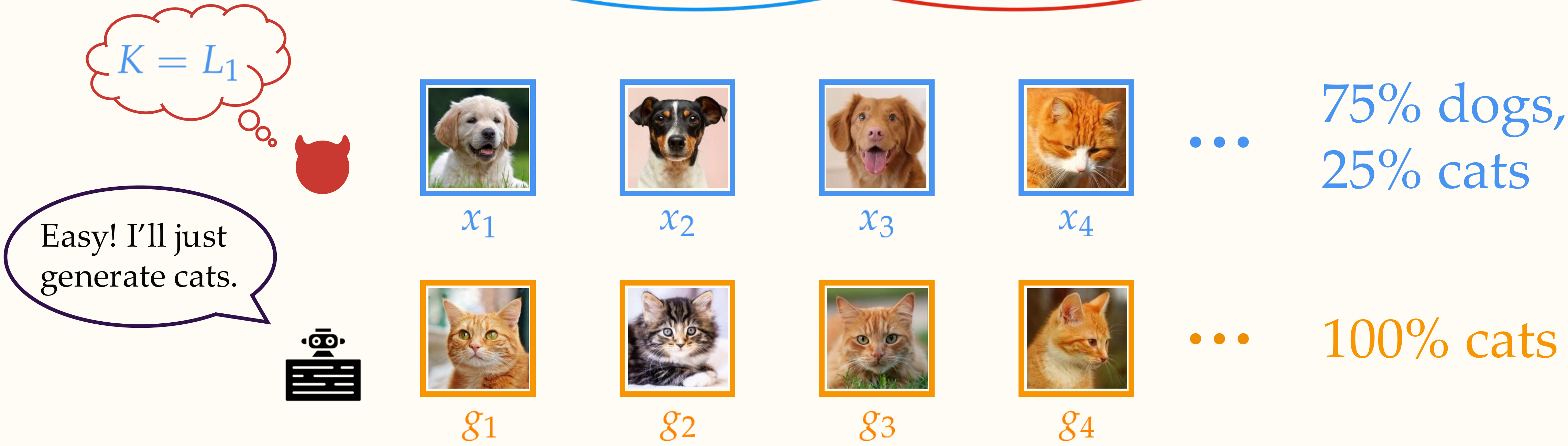

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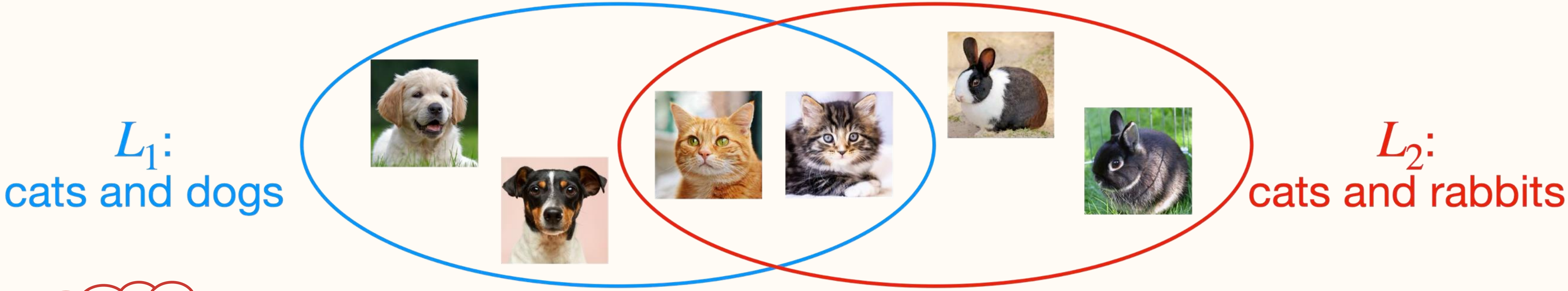

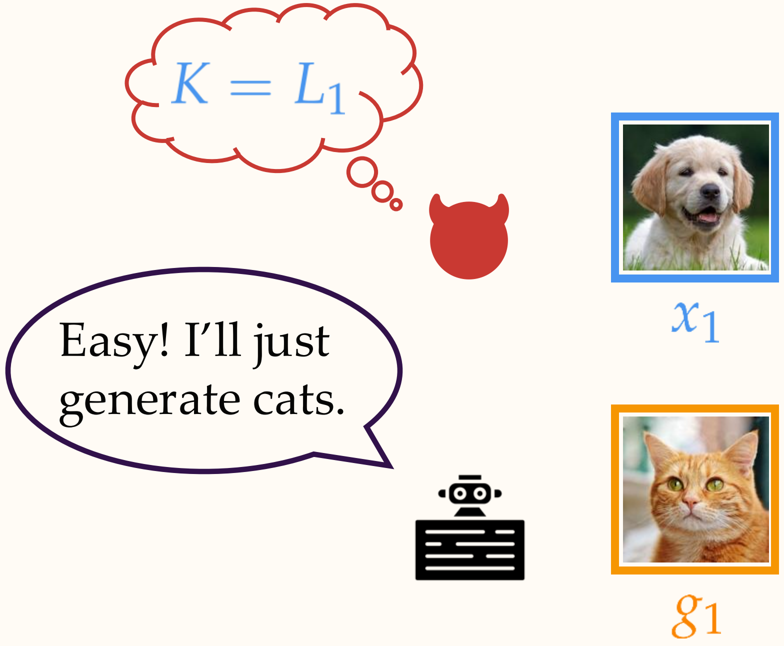

Even when generations are consistent, they may not meaningfully resemble the data stream.

Representative Generation

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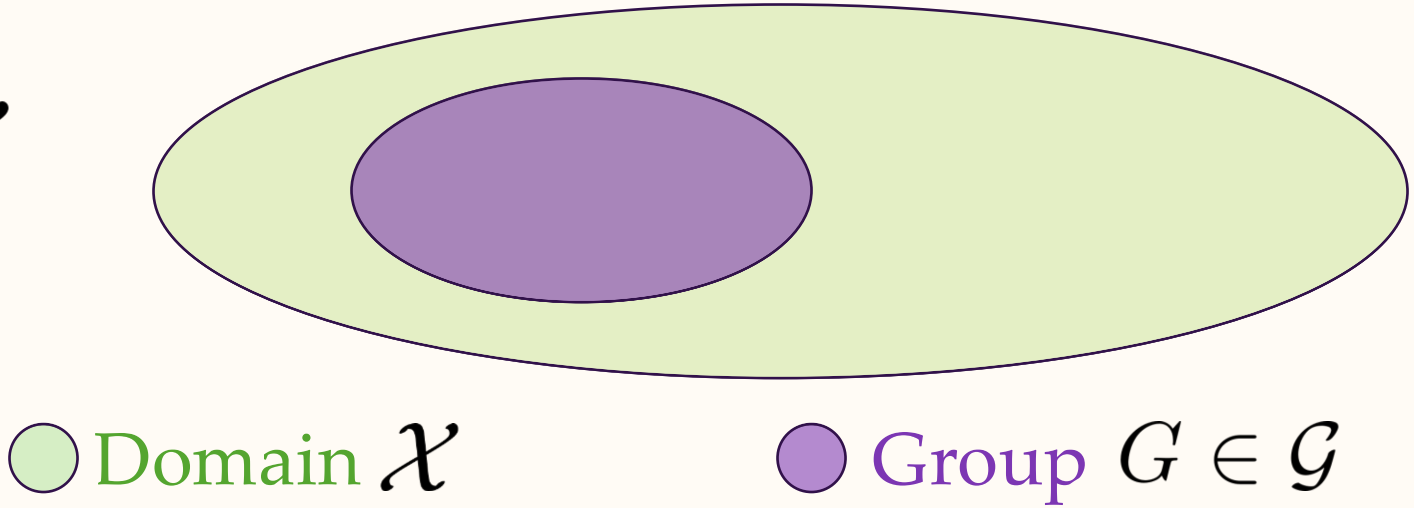
$$\mathcal{G} \subseteq 2^{\mathcal{X}}$$



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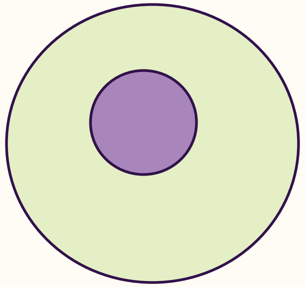

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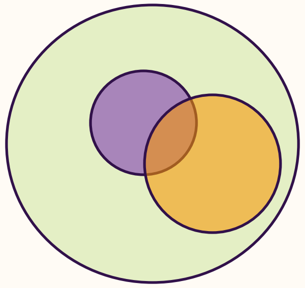

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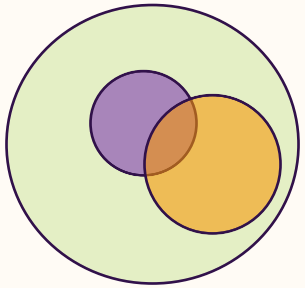

$$\Pr_{x \sim \mu_t} [x \in G]$$

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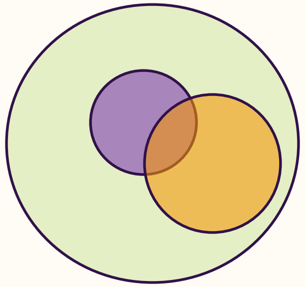
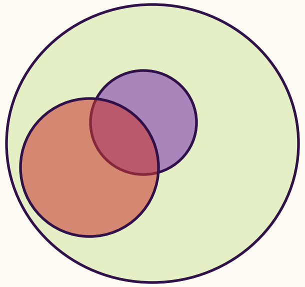


$$\Pr_{x\sim\mu_t}[x \in G] \approx$$

Proportion of G in adversary stream thus far.



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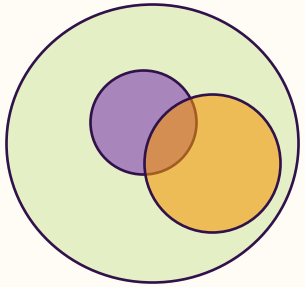
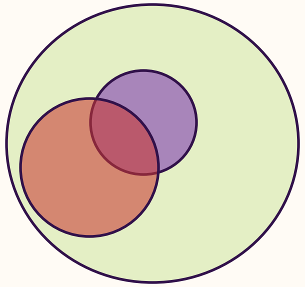


$$\Pr_{x\sim\mu_t}[x \in G] \approx \frac{1}{|x_{1:t-1}|}\sum_{x_i \in x_{1:t-1}} \mathbf{1}[x_i \in G]$$



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Representative Generation

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For which group collections and language classes can we representatively generate?

Results

Informal Theorem Any countable language class and countable group collection (subject to a minor assumption) can be representatively generated in the limit.

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But, not possible with only membership queries to languages and groups…

Also…

- Characterize representative uniform and non-uniform generatability for finite, disjoint, groups.

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Problem: Even when it becomes critical, the true language isn't guaranteed to allow the generator to pass group tests while playing only from the language support.

We show: Eventually, the generator *can* satisfy all group constraints while generating only from the support of the true language. Thus, the true language will not get filtered out!

Future Directions

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- Uniform/non-uniform representative generatability: going beyond finite, disjoint, groups.

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- Understanding representative generation in the limit beyond countable classes.

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- How do we deal with groups that may change and shift over time?

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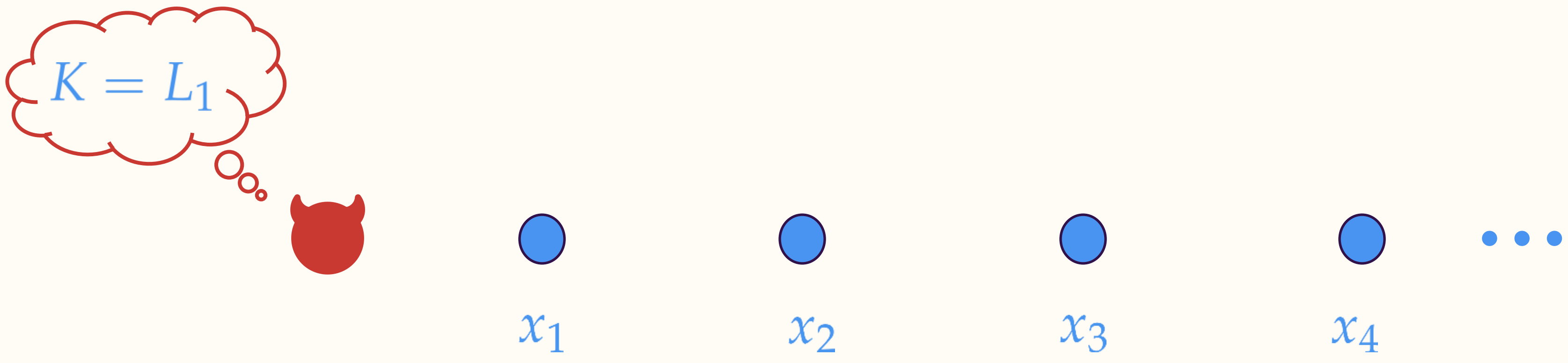
   Generation from Noisy Examples, [Ananth Raman, Vinod Raman]

   a. Model
   b. Results
   c. Future Directions

Generating from Noisy Examples

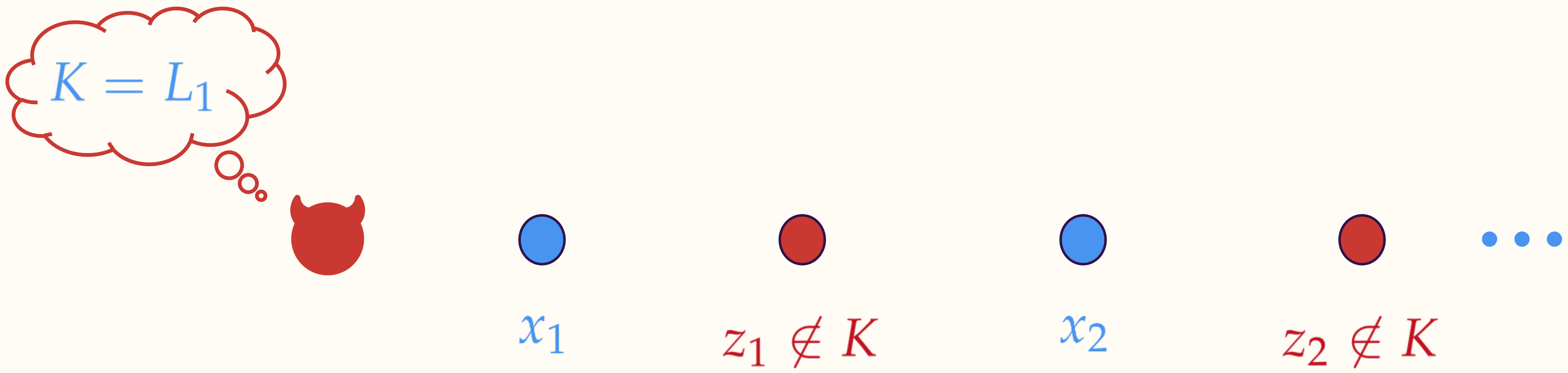
Ananth Raman, Vinod Raman (ICML, 2025)

Model



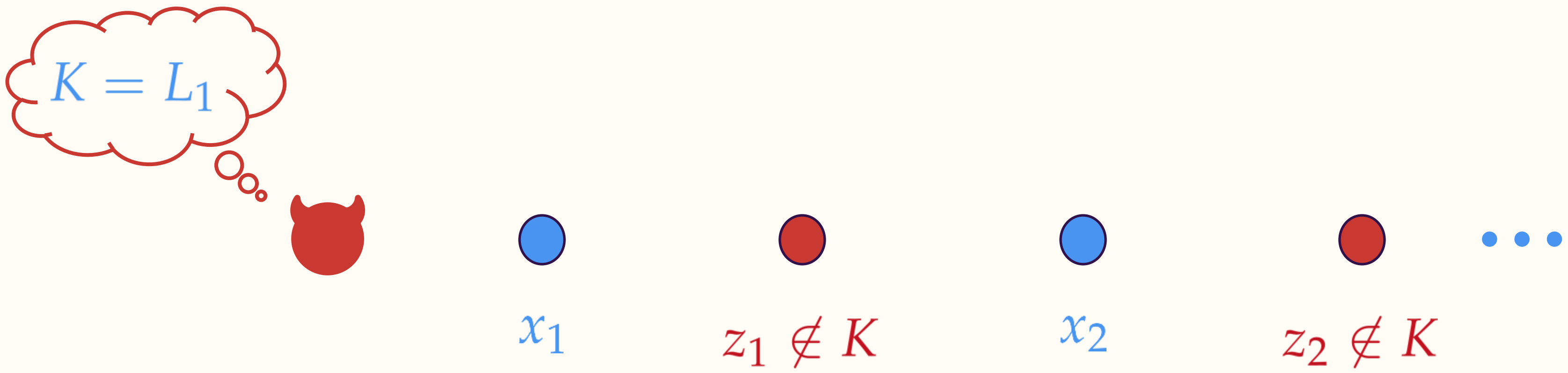
Thus far, adversaries are guaranteed to always output datapoints from the true language.

Model



- What if some points are noisy, and not from the true language?

Model



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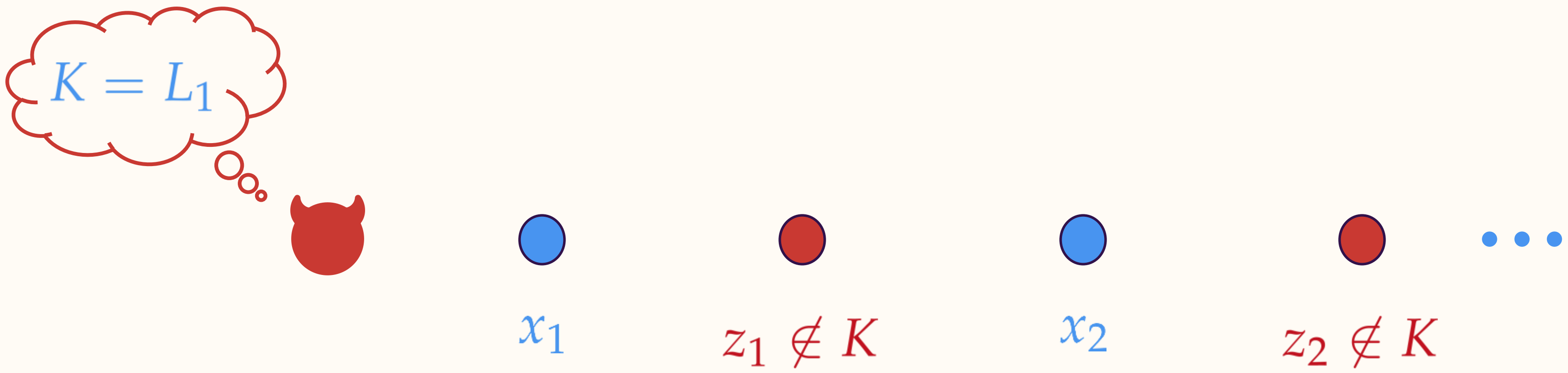
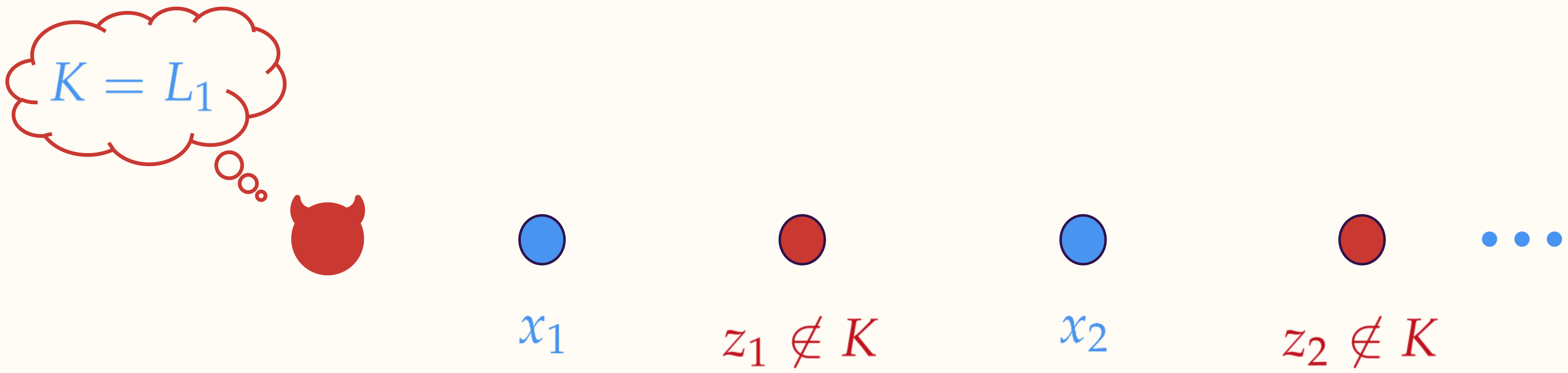


- What if some points are noisy, and not from the true language?
- Important for capturing real-world data settings
  - E.g., internet data containing hallucinations of other LLMs

Model



New Generation Setting: We allow the adversary to insert a *finite* number of noisy datapoints into the stream.

Model

1. Adversary picks target $\boldsymbol{K = L_{i^\star}}$ and enumeration $z_1, z_2, \ldots$
2. Adversary picks $n^* \in \mathbb{N}$, and inserts at most n^* negative examples into the enumeration to obtain stream $x_1, x_2, \ldots$.
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The same noise model studied in works on language *identification* in the limit [Schäfer, 1985; Fulk & Jain, 1989; Baliga et al., 1992; ...]

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Can also define notions of uniform, non-uniform noisy generatability (see paper for details)

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Taste of the Theorem Proof

Informal Theorem If a class $\mathcal{L}$ is (noiseless) non-uniformly generatable, then it is noisily generatable in the limit.

Goal: Use a blackbox noiseless non-uniform generator to generate in the limit with noise.

$$Q(x_1, x_2, \ldots, x_{t-1}) \to g_t$$

Non-uniform generator

In true language after d^* unique elements

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Problem: guarantee breaks down when data stream corrupted.

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With a few tweaks to make sure no duplicates are generated, this approach generates in the limit!

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- Can noisy generation in the limit be achieved with only membership oracle access? Cf. [KM'24]
- Is there a reasonable definition of agnostic generatability for language generation?