Neural sequence generation

DATA 598

Sean Welleck | 03.03.2022

Motivation

Modeling and generating language

- Language encapsulates ideas.
- Factual knowledge
  - *Molly Seidel won the* $\boxed{\qquad}$ *medal in the 2020 Olympic marathon.*
- State of the art GPT-3 **language model**: Today's lecture
  - **I am a highly intelligent question answering bot.**

    Q: Who was president of the United States in 1955?
    A: Dwight D. Eisenhower was president of the United States in 1955.

    Q: Molly Seidel won which medal in the 2020 Olympic marathon?
    A: Molly Seidel won a bronze medal in the 2020 Olympic marathon.

Motivation

Modeling and generating language

- Language encapsulates ideas.
- Common sense
    - *I tipped the bottle. As a result,*
- State of the art GPT-3 language model:
    - **I will continue your sentence based on my common-sense understanding of the world:**

      I tipped the bottle. As a result, the drink spilled out.

Motivation

Modeling and generating language

- Language encapsulates ideas.
- Logical reasoning
  - *Alice purchased three widgets, and Bob purchased three times as many. In total, Alice and Bob purchased ______ widgets.*
- State of the art GPT-3 language model:
  - **I can solve numerical reasoning problems.**

    Problem: The dog had four meals every day for three weeks.
    Answer: In total, the dog had 4 * 7 * 3 meals.

    Problem: Two students worked for 8 hours, and a third student worked for 3 hours.
    Answer: In total, the students worked 2 * 8 + 3 hours.

    Problem: Alice purchased three widgets, and Bob purchased three times as many.
    Answer: In total, Alice and Bob purchased 9 widgets.

AI is not solved yet

Motivation

Modeling and generating language

- **Generating** language is **useful**.
- Machine translation
    - **Translate this into 1. French, 2. Spanish and 3. Japanese:**

      What rooms do you have available?

      1. Quels sont les chambres disponibles?
      2. ¿Cuáles son las habitaciones disponibles?
      3. 何とか部屋がありますか?

Motivation

Modeling and generating language

- **Generating** language is **useful**.
- Dialogue
    - **You: What have you been up to?**
      Friend: Watching old movies.
      You: Did you watch anything interesting?
      Friend: Yes, I watched The Omen and Troy.

Motivation

Modeling and generating sequences (text, code, …)

- **Generating** ~~language~~ *sequences* is **useful**.
- Programming assistants

```python
# Python 3.7

def randomly_split_dataset(folder, filename, split_ratio=[0.8, 0.2]):
    df = pd.read_json(folder + filename, lines=True)
    train_name, test_name = "train.jsonl", "test.jsonl"
    df_train, df_test = train_test_split(df, test_size=split_ratio[1], random_state=42)
    df_train.to_json(folder + train_name, orient='records', lines=True)
    df_test.to_json(folder + test_name, orient='records', lines=True)
randomly_split_dataset('finetune_data/', 'dataset.jsonl')

# An elaborate, high quality docstring for the above function:
"""
```

```
    Splits a dataset into train and test sets.

    Args:
        folder (str): The folder where the dataset is located.
        filename (str): The name of the dataset file.
        split_ratio (list): The ratio of train/test split.

    Returns:
        None
```

Motivation

Modeling and generating sequences (text, code, …)

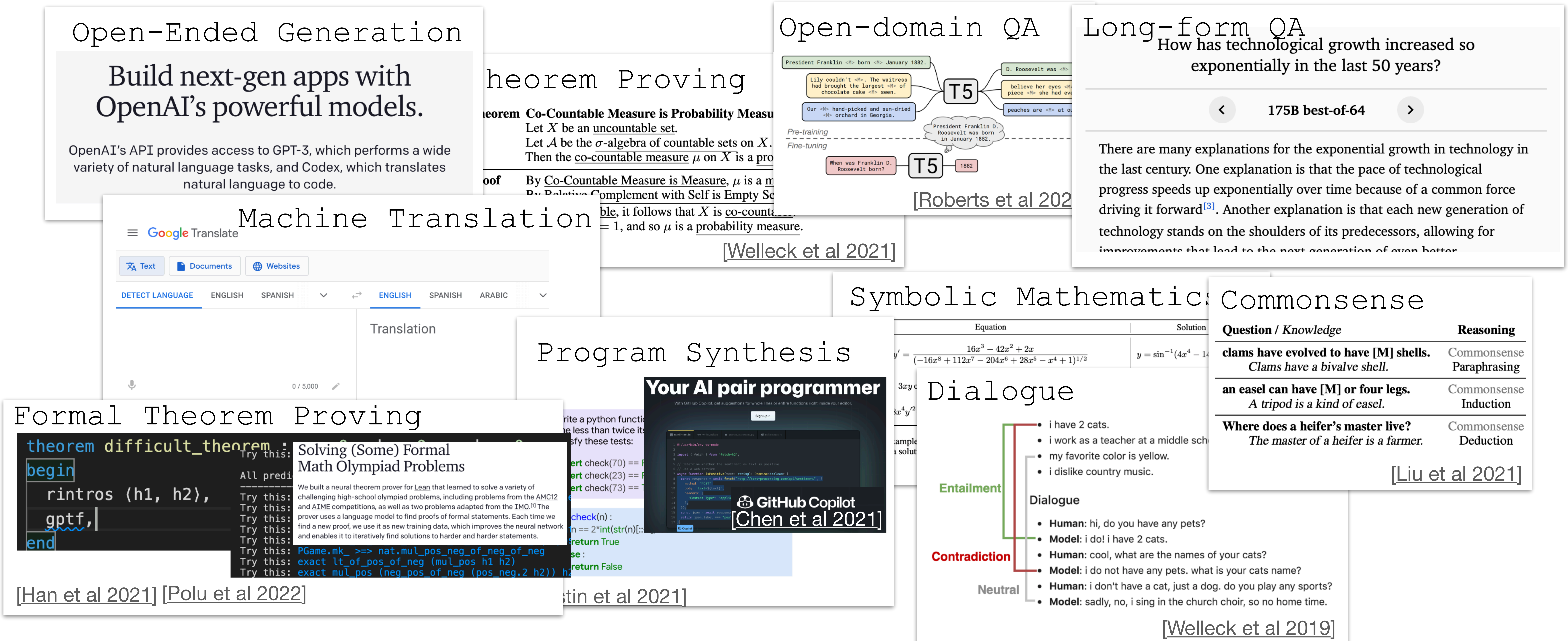
- **Generating** ~~language~~ *sequences* is **useful**.
- Education
    - **I'm an intelligent tutor. Tell me where you're stuck and I'll give you a hint.**

      Q: I'm having trouble proving that the sum of two odd numbers is even.
      A: Make the sum of two odd numbers into the form 2k. Finally, use the definition of an even number.

      Q: I'm having trouble proving that if x is even, x + 5 is odd.
      A: Use a proof by contradiction. Assume that x + 5 is even. This means that x + 5 can be written as 2k for some integer k. Now, subtract 5 from each side of the equation. This gives us x = 2k - 5. But this is a contradiction because x is even and 2k - 5 is odd.

Today's lecture

A common *language modeling* recipe underlies all of these applications.



Today's lecture

Modeling and generating sequences

- **A common *language modeling* recipe underlies all of these applications.**
- Today's lecture:
    - What is a language model?
    - Generating sequences with a language model.
- Lab: generate sequences with a real-world language model.

Modeling	Learning	Decoding

What is a language model?

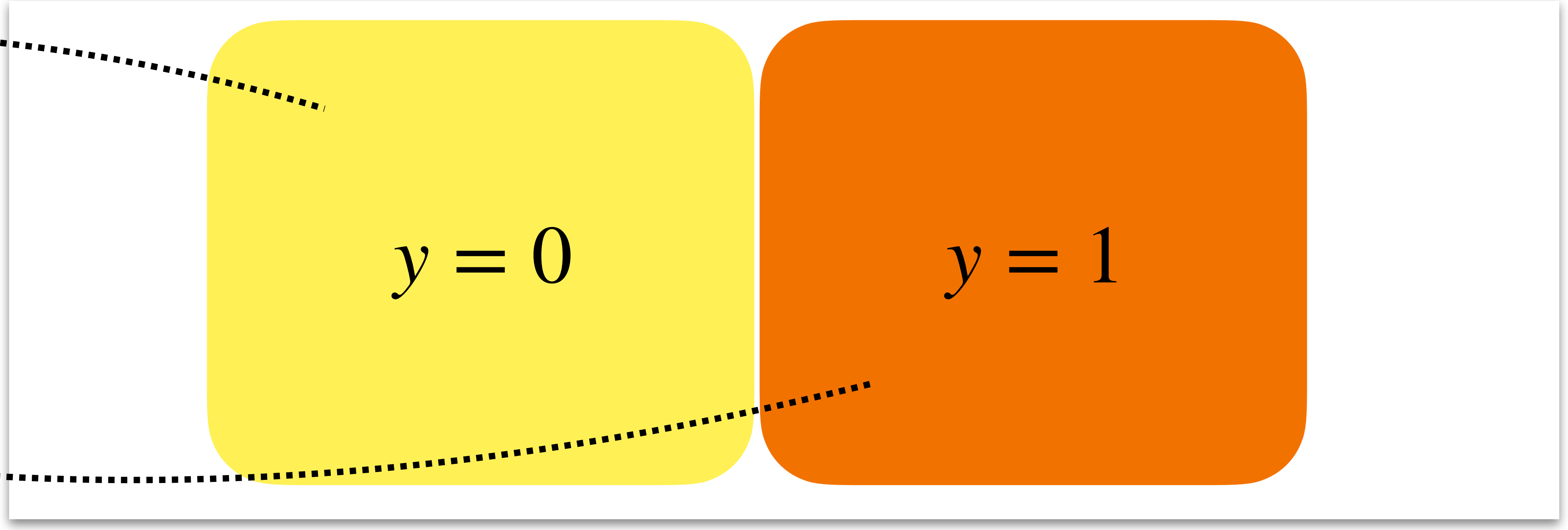
Setup

- $\mathbf{y}_{1:T} = (y_1, y_2, \ldots, y_T)$, where $y_t \in V$
  - $\mathbf{y}_{1:T}$ **sequence** e.g. `the cat sat .` T can vary.
  - y_t **token** e.g. `cat`
  - V **vocabulary** e.g. `{a, b, …, zebra, …}`
- $\mathbf{y} \in \mathcal{Y}$, $\mathcal{Y}$ set of all sequences

What is a language model?

Language model

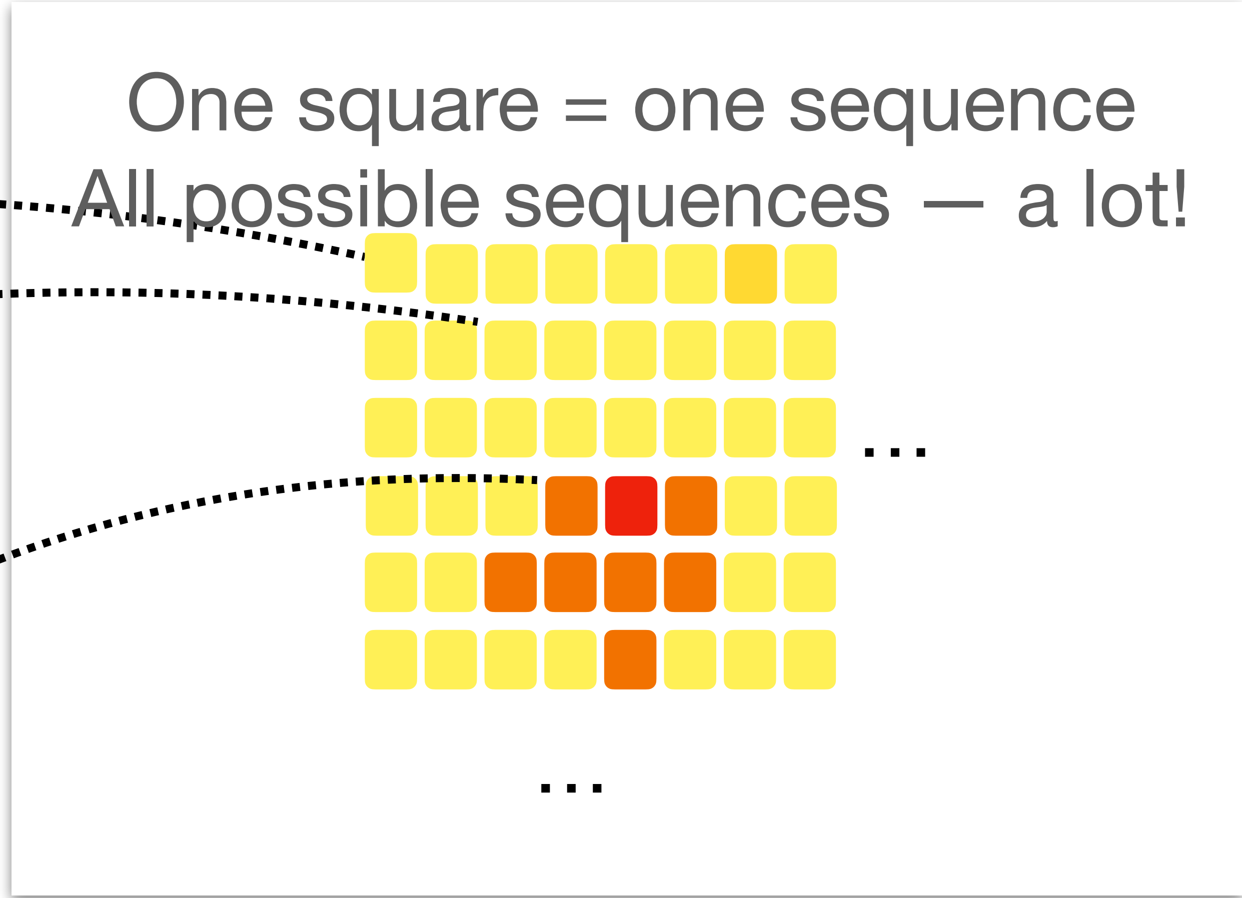
- A language model is a probability distribution over all sequences
  - $p(\mathbf{y})$
- Example probability distribution: **biased coin**
  - $p(y) = \begin{cases} 0.4 & y \text{ is } 0 \\ 0.6 & y \text{ is } 1 \end{cases}$



What is a language model?

Language model

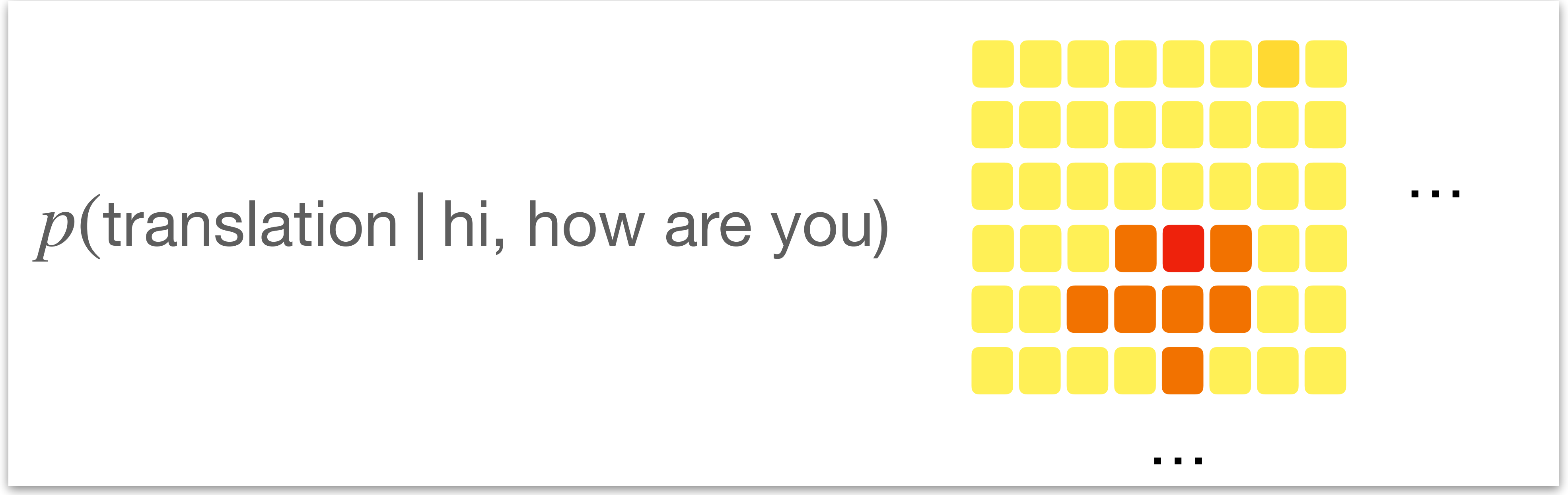
- A language model is a probability distribution over all sequences
    - $p(\mathbf{y})$
- Example language model
    - $p(\mathbf{y}) =$ 0.000013 if $\mathbf{y}$ is `a.`
      0.000001 if $\mathbf{y}$ is `aa.`
      …
      0.019100 if $\mathbf{y}$ is `a cat sat.`
      …

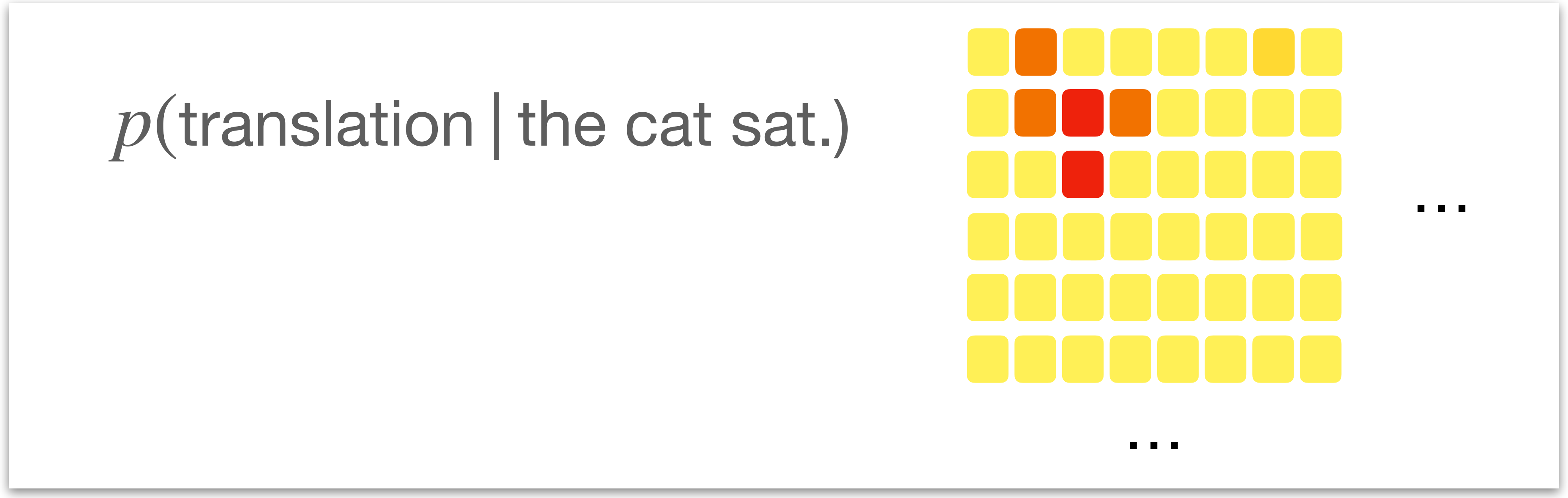


What is a language model?

Sequence-to-sequence with a language model

- A language model can accept an **input** by conditioning on an input prefix:
  - $p(\mathbf{y}_{k+1:T} | \mathbf{y}_{1:k})$
  - Machine translation:
    - Prefix : sentence in English
      Continuation : sentence in Japanese
  - General task:
    - Prefix : instructions, examples, start of output
      Continuation: output





What is a language model?

Sequence-to-sequence with a language model

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Translate this into 1. French, 2. Spanish and 3. Japanese:

What rooms do you have available?

1. Quels sont les chambres disponibles?
2. ¿Cuáles son las habitaciones disponibles?
3. 何とか部屋がありますか?

- How do we *learn* a language model from data?
- How do we *generate* text from a language model?

Modeling

The building blocks | Modeling

Autoregressive language model

- First step: use the chain rule of probability:

- $$p(\mathbf{y}_{1:T}) = \prod_{t=1}^{T} p(y_t \mid \mathbf{y}_{<t})$$

  - *p*(the cat sat <end>)=
    p(the)*p*(cat | the)*p*(sat | the cat)*p*(<end> | the cat sat)

The building blocks | Modeling

Modeling

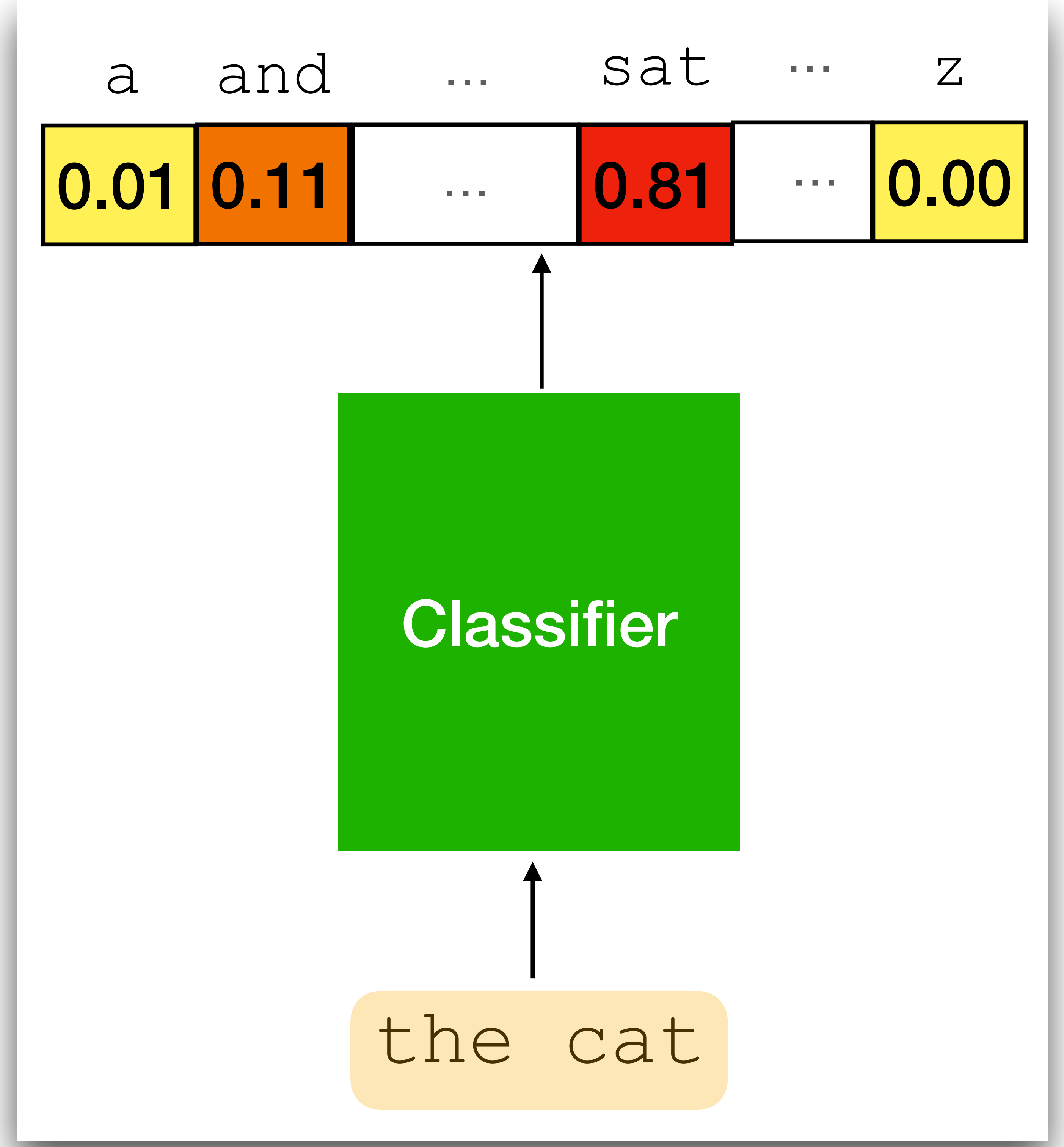
Autoregressive language model

- Language modeling is reduced to **classification**
- $$p(\mathbf{y}_{1:T}) = \prod_{t=1}^{T} p(\underbrace{y_t}_{\text{Next Token}} \mid \underbrace{\mathbf{y}_{<t}}_{\text{Previous Tokens}})$$
   - $p($`the cat sat <end>`$)=$ $p($`the`$)p($`cat` $|$ `the`$)p($`sat` $|$ `the cat`$)p($`<end>` $|$ `the cat sat`$)$
- Sequence probability = product of **next-token** probabilities

The building blocks | Modeling

Autoregressive language model

- Language modeling is reduced to **classification**
  - $p(\mathbf{y}_{1:T}) = \prod_{t=1}^{T} p(\underbrace{y_t}_{\text{Next Token}} \mid \underbrace{\mathbf{y}_{<t}}_{\text{Previous Tokens}})$
- $p(y_t \mid \mathbf{y}_{<t})$
  - Input: $\mathbf{y}_{<t} \in V \times V \times \ldots V$
    Output: probability distribution over V
  - Target: $y_t \in V$



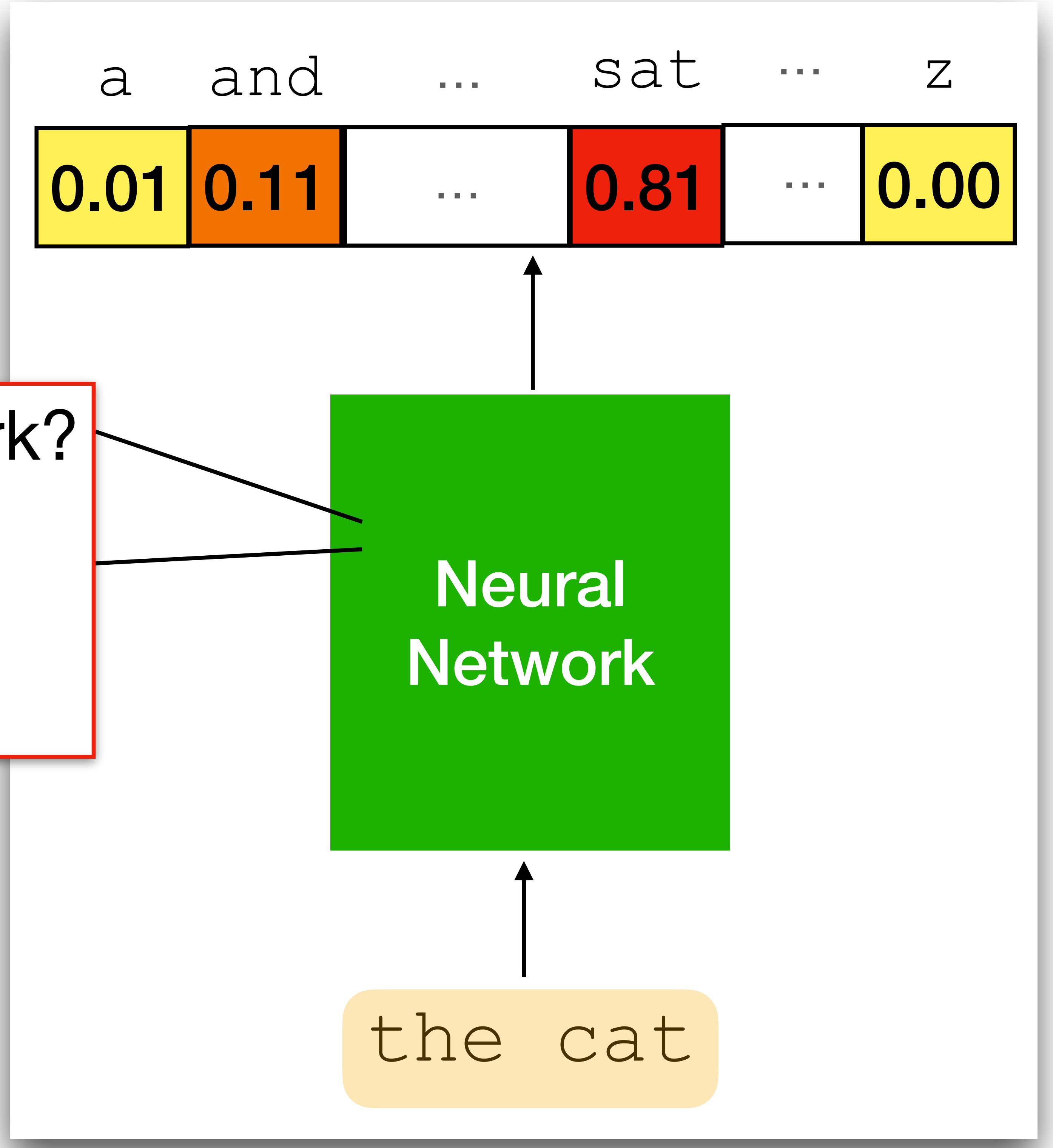
Modeling

The building blocks | Modeling

Neural autoregressive language model

- Use a neural network for language modeling
  - $$p_\theta(\mathbf{y}_{1:T}) = \prod_{t=1}^{T} p_\theta(\underbrace{y_t}_{\text{Next Token}} \mid \underbrace{\mathbf{y}_{<t}}_{\text{Previous Tokens}})$$
  - $p_\theta(y_t \mid \mathbf{y}_{<t})$
    - Input: $\mathbf{y}_{<t} \in V \times V \times \ldots V$
      Output: probability distribution over V
    - Target: $y_t \in V$

- What kind of neural network?
- How do we learn the parameters θ?

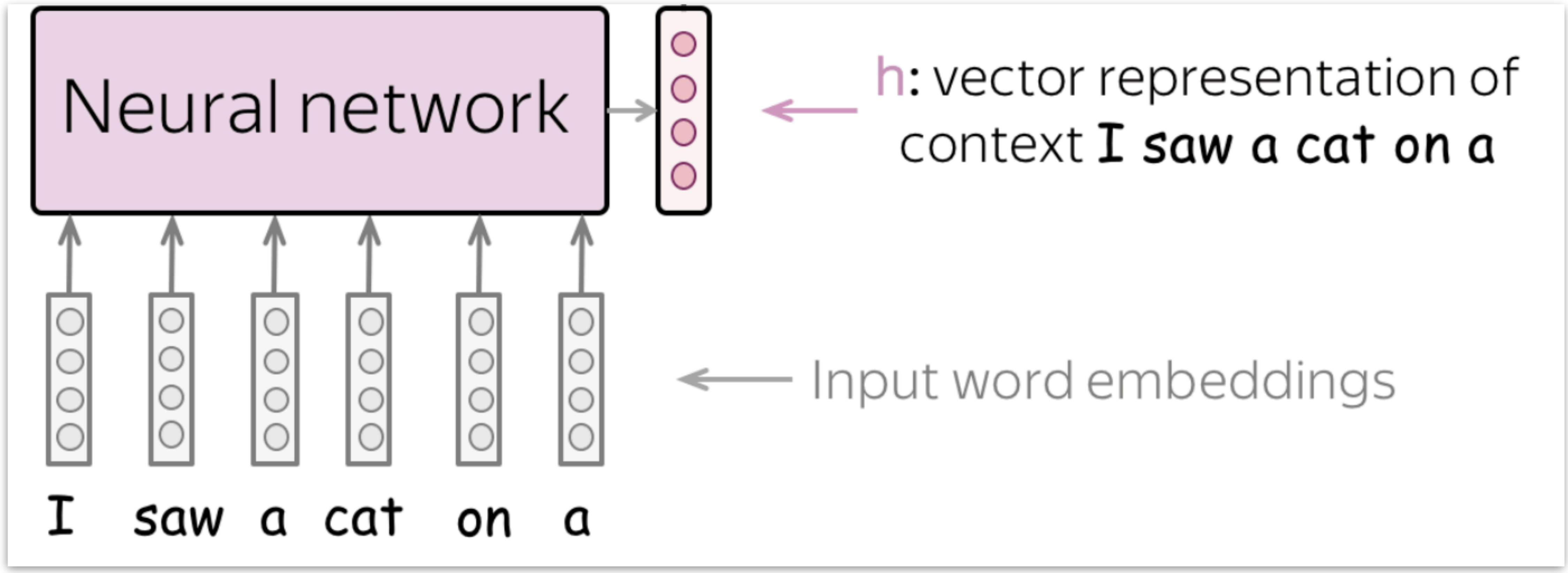


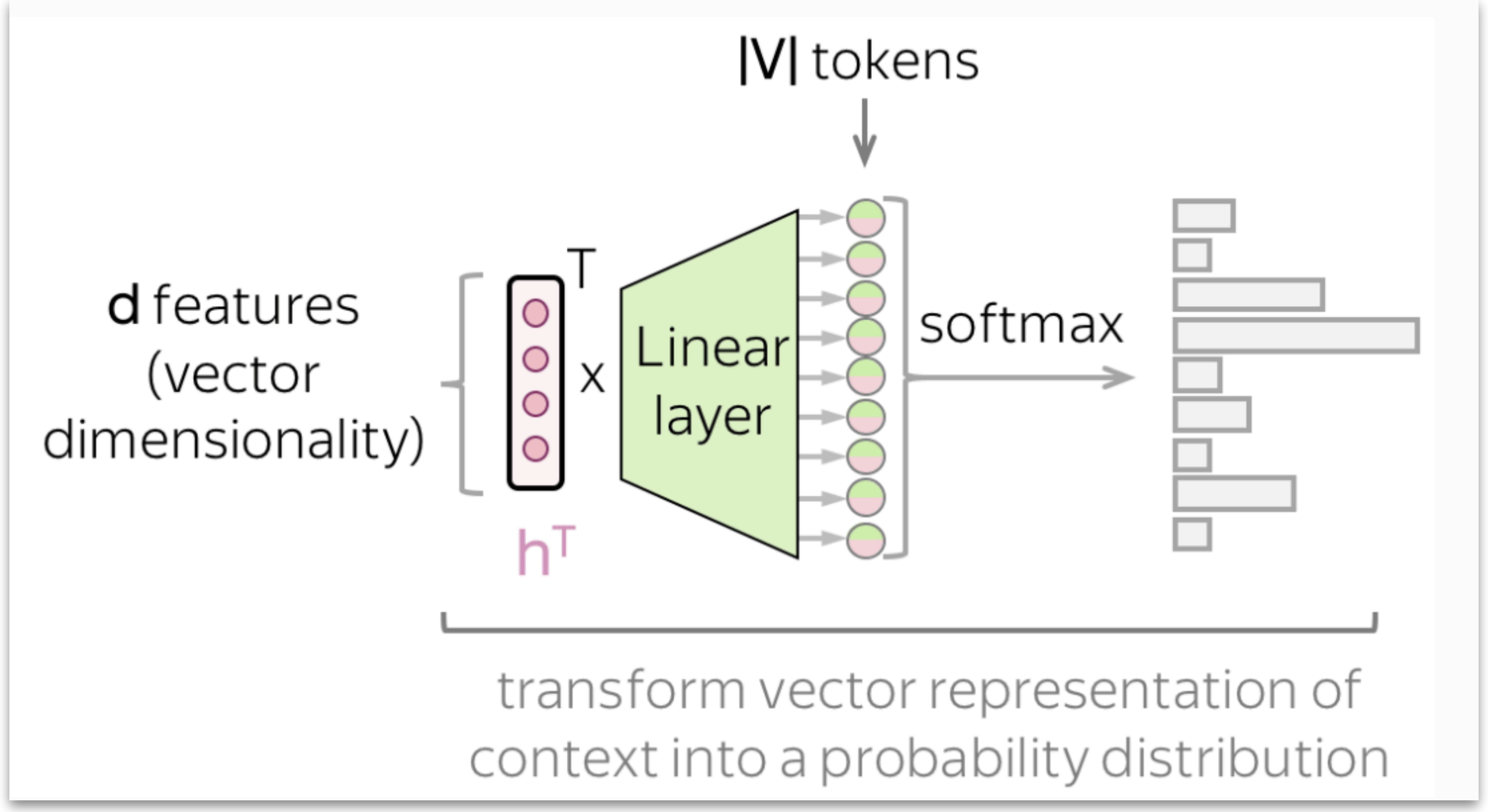
The building blocks | Modeling

What kind of neural network?

Modeling

- Want: $p_\theta(y_t \mid y_1, \ldots, y_{t-1})$
  - Encode context into a vector:
    - $h_t = f_\theta(y_1, \ldots, y_{t-1}), h_t \in \mathbb{R}^d$
  - Transform into |V| token scores:
    - $s_t = Eh_t$, where $s_t \in \mathbb{R}^{|V|}, E \in \mathbb{R}^{(|V| \times d)}$
  - Take the softmax to get a probability vector
    - $p_\theta(\cdot \mid y_1, \ldots, y_{t-1}) = \text{softmax}(s_t)$





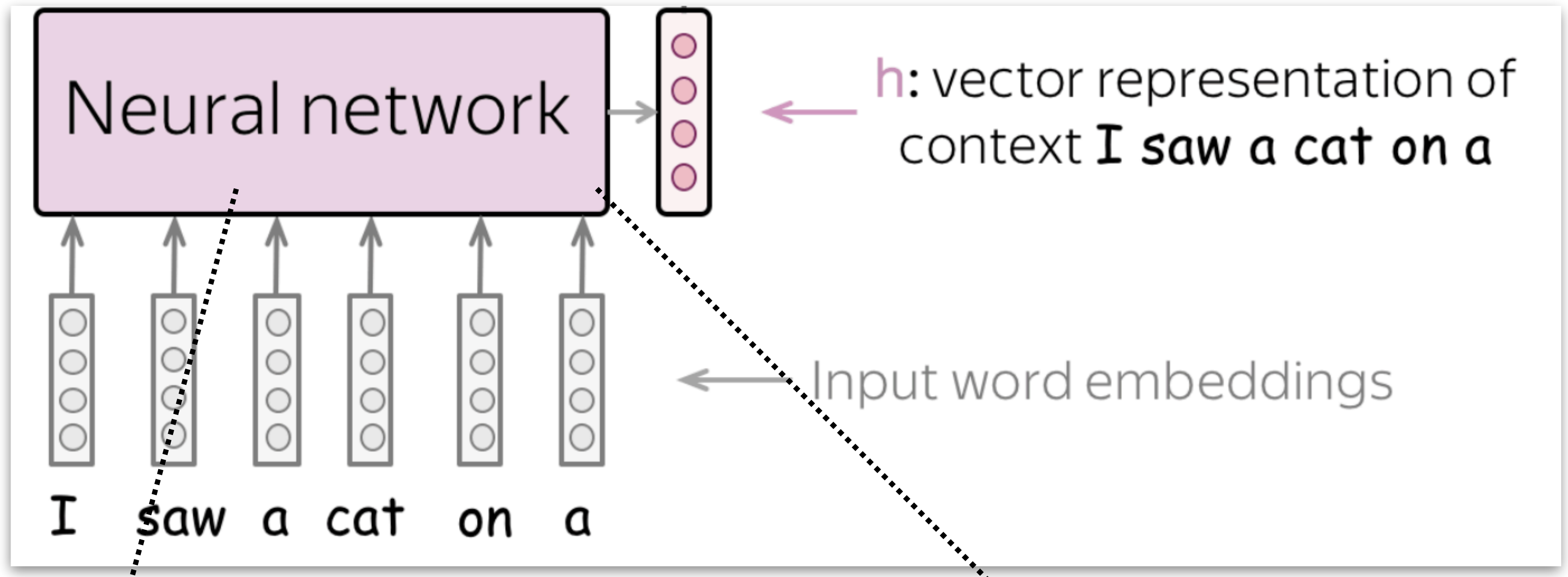
Diagrams: https://lena-voita.github.io/nlp_course/language_modeling.html

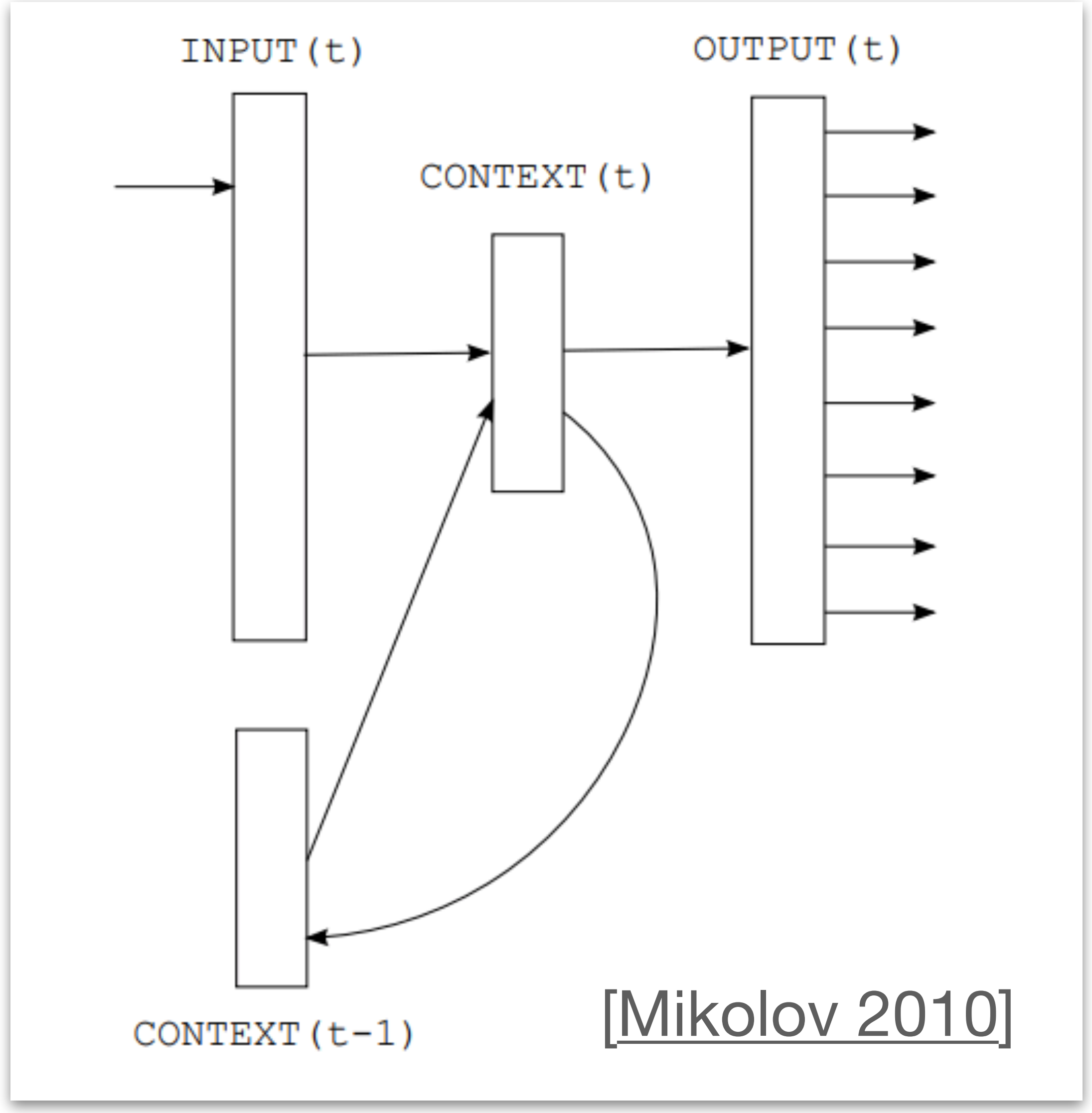
Modeling

The building blocks | Modeling

What kind of neural network?

- Common choices for the neural network:
    - Recurrent neural network
    - Feedforward + attention (transformer)
- *Further details are out of scope for this lecture*!





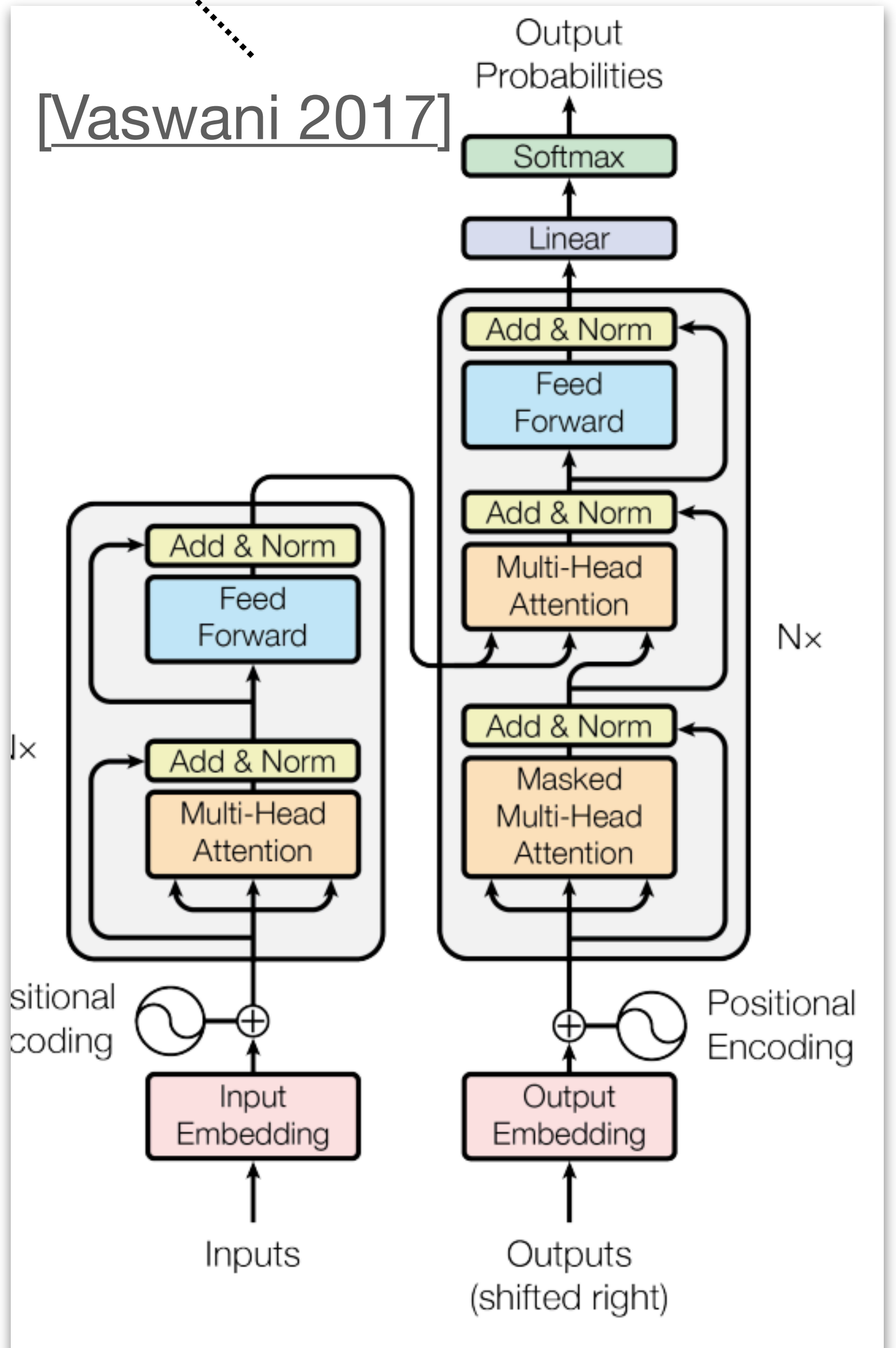


Figure 1: The Transformer - model architecture.

The building blocks | Learning

How do we learn the parameters θ?

- Collect a dataset of sequences $D = \{\mathbf{y}_1, \ldots, \mathbf{y}_N\}$
  - D: a book
  - D: all text on the internet
  - …
- Tokenize each sequence, $\mathbf{y}_i = (y_1, \ldots, y_{T_i})$
  - We'll see this concretely in the lab!

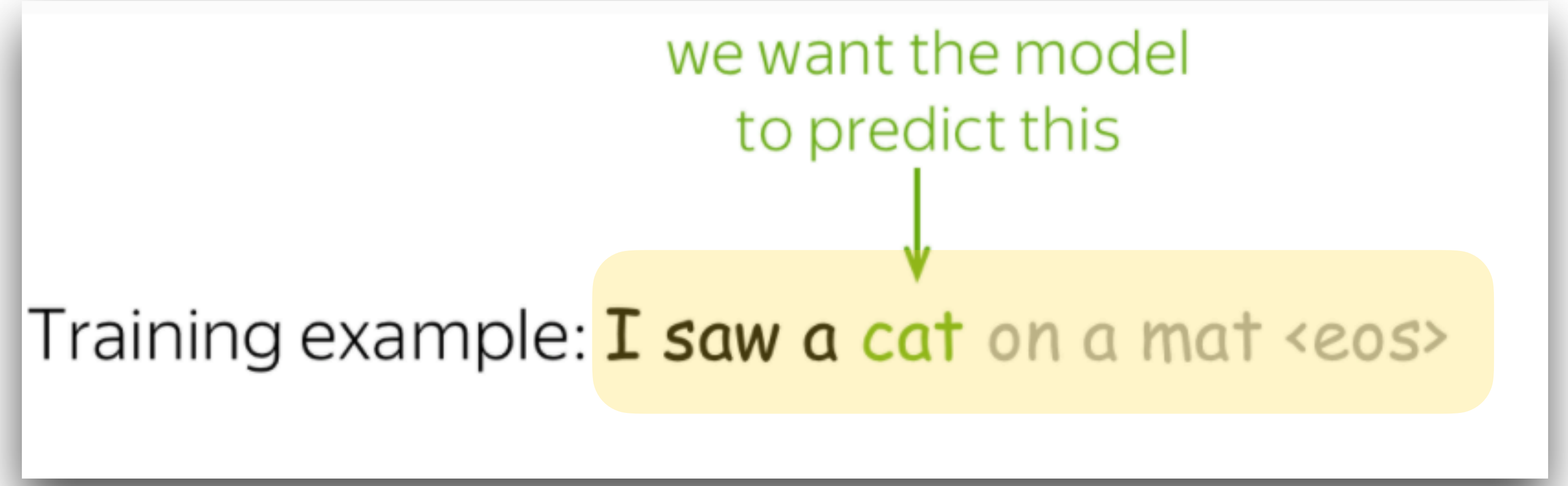
The building blocks | Learning

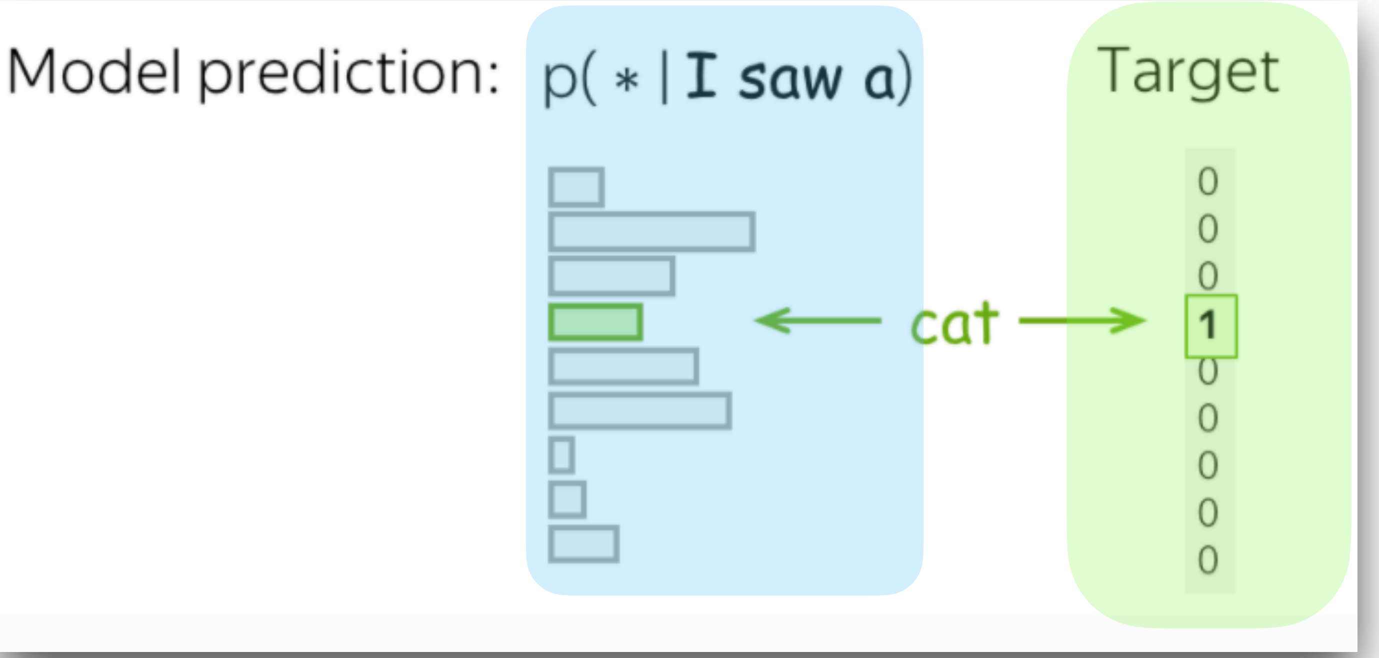
How do we learn the parameters θ?

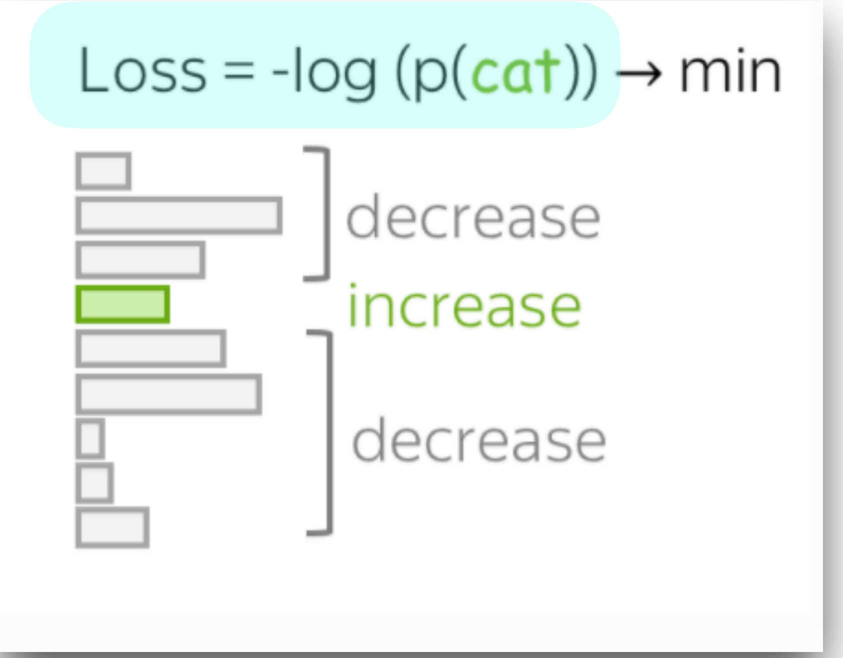
- For each training sequence $\mathbf{y} = (y_1, \ldots, y_T)$ and step t:
  - Model predicts $p_\theta^t(\cdot \mid \mathbf{y}_{<t}) \in \Delta^V$
  - Target is $p_*^t = \begin{cases} 1 & y_t \\ 0 & \text{otherwise} \end{cases} \in \Delta^V$
  - Use **cross-entropy loss**:

$$\mathscr{L}_t = -\sum_{y \in V} p_*^t(y) \log p_\theta^t(y \mid \mathbf{y}_{<t})$$

$$= -\log p_\theta^t(y_t \mid \mathbf{y}_{<t})$$







Diagrams: https://lena-voita.github.io/nlp_course/language_modeling.html

The building blocks | Learning

Why cross-entropy loss?

- **Classifier view:**
  - We've used cross-entropy loss to train classifiers previously in the course…
- **Estimation view:** Loss summed over the entire dataset:

$$\min_{\theta} - \sum_{\mathbf{y} \in D} \sum_{t} \log p_{\theta}(y_t \mid \mathbf{y}_{<t})$$

  - $\equiv \max_{\theta} \sum_{\mathbf{y} \in D} \log p_{\theta}(\mathbf{y})$
  - Finds parameters that make the observed data *D* most probable; i.e. **maximum likelihood estimation**

Learning

The building blocks | Learning

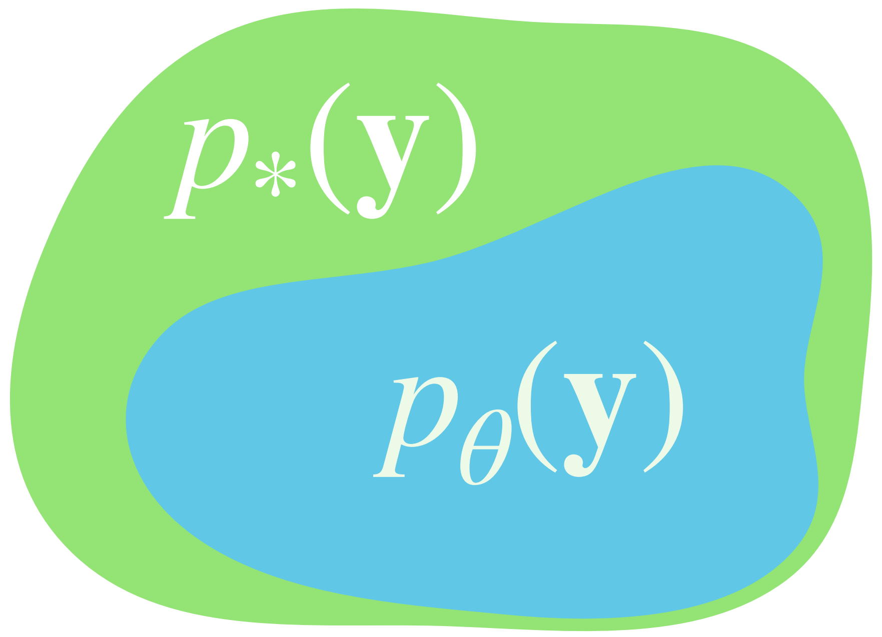
Why cross-entropy loss? | Distribution matching view

- Makes p_θ match an underlying 'true' distribution $p_*(\mathbf{y})$ ·············· E.g. distribution that generated all internet text…

$$
\begin{aligned}
\min_\theta D_{KL}(p_* \,||\, p_\theta) &= \min_\theta - \sum_{\mathbf{y}\in\mathcal{Y}} p_*(\mathbf{y}) \log \frac{p_\theta(\mathbf{y})}{p_*(\mathbf{y})} \\
&\equiv \min_\theta - \sum_{\mathbf{y}\in\mathcal{Y}} p_*(\mathbf{y}) \log p_\theta(\mathbf{y}) + \text{const} \\
&= -\mathbb{E}_{\mathbf{y}\sim p_*} \log p_\theta(\mathbf{y}) \\
&\approx \min_\theta - \frac{1}{|D|} \sum_{\mathbf{y}\in D} \log p_\theta(\mathbf{y}) \\
&\equiv \max_\theta \sum_{\mathbf{y}\in D} \log p_\theta(\mathbf{y})
\end{aligned}
$$

········ Definition of expected value

········ "Monte-Carlo" approximation of expected value



The building blocks | Learning

Why cross-entropy loss?

- Scaling laws: more {compute, data, parameters} $\Longrightarrow$ better loss

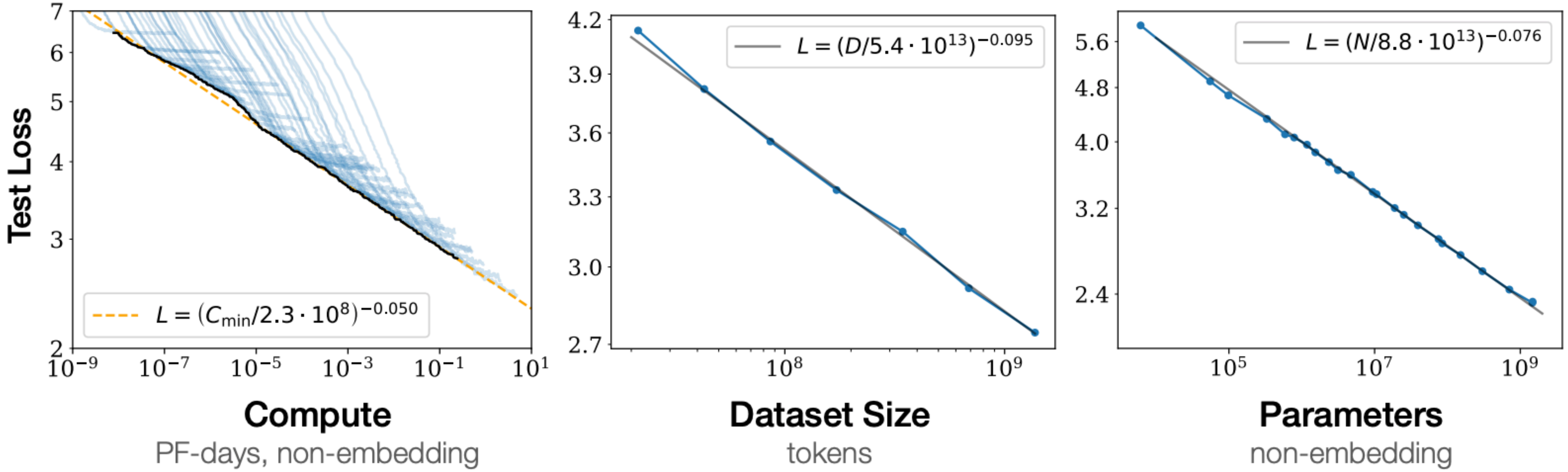


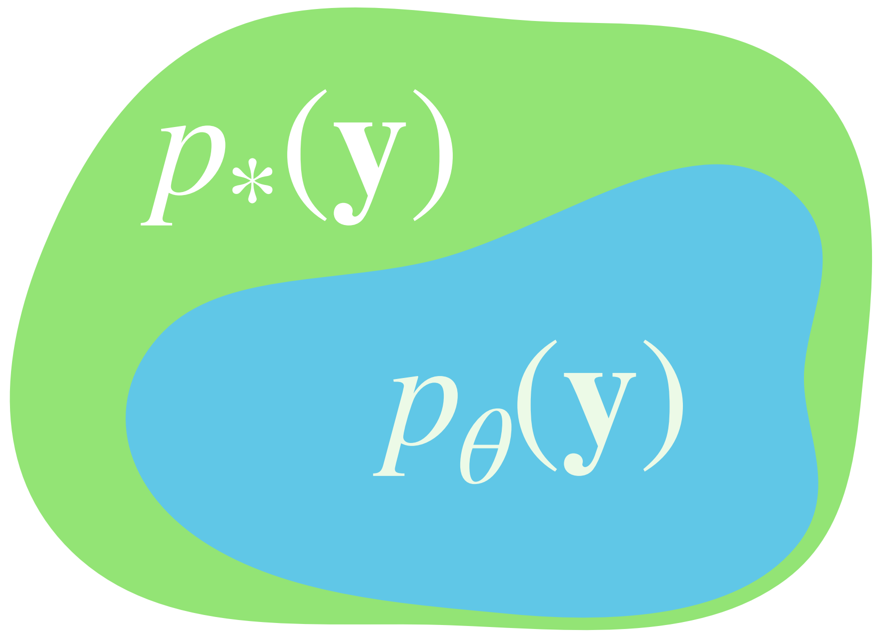
Figure 1 Language modeling performance improves smoothly as we increase the model size, datasetset size, and amount of compute[2] used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.

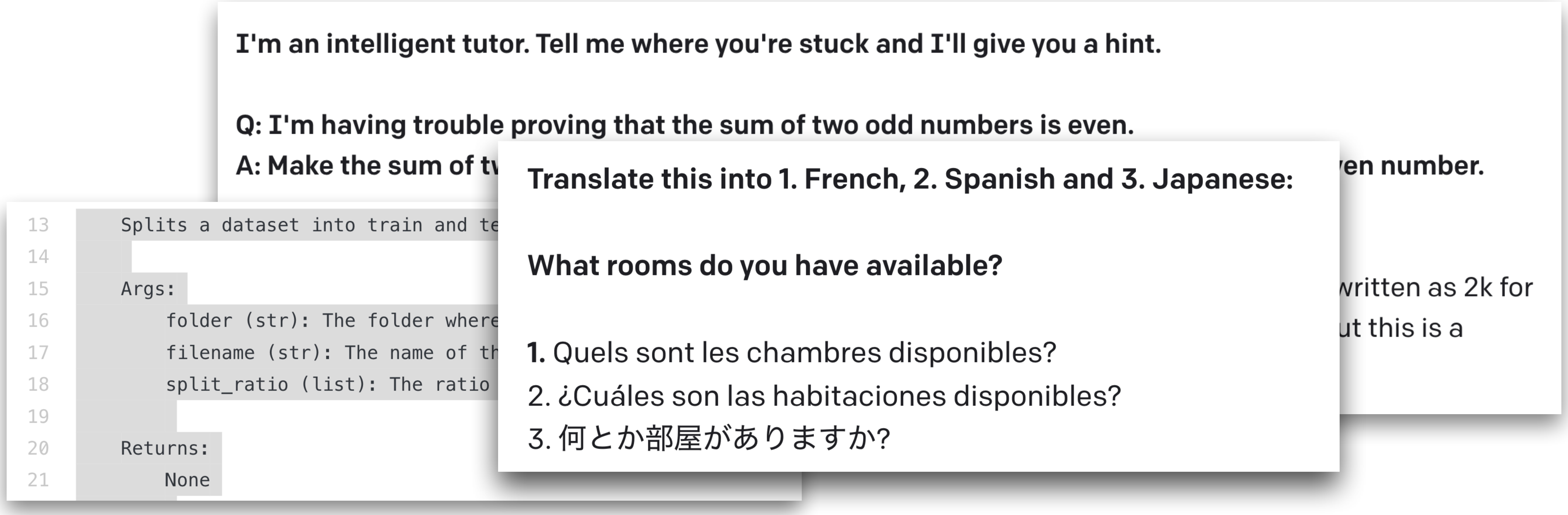
[Kaplan et al 2020]

The building blocks | Recap

Recap

- We've now *learned* a neural language *model* p_θ from data.
    - We have a distribution over all sequences.
- Next: To **generate** text, we use a *decoding* algorithm.





Building blocks | Decoding

Generating sequences from our model

- **Goal**: generate a continuation $\mathbf{y}$ given a model p_θ
- We want to generate $\mathbf{y} = (y_1, \ldots, y_T)$, starting from $y_0 = \langle start \rangle$
  - We generate one-token, feed it into the model, and repeat:
    - $y_1 = \text{generate}(p_\theta(y \mid y_0))$
    - $y_2 = \text{generate}(p_\theta(y \mid y_0, y_1))$
    - $y_3 = \text{generate}(p_\theta(y \mid y_0, y_1, y_2))$
    - … => $(y_1, \ldots, y_T)$

Decoding

Building blocks | Decoding

Generating sequences from our model

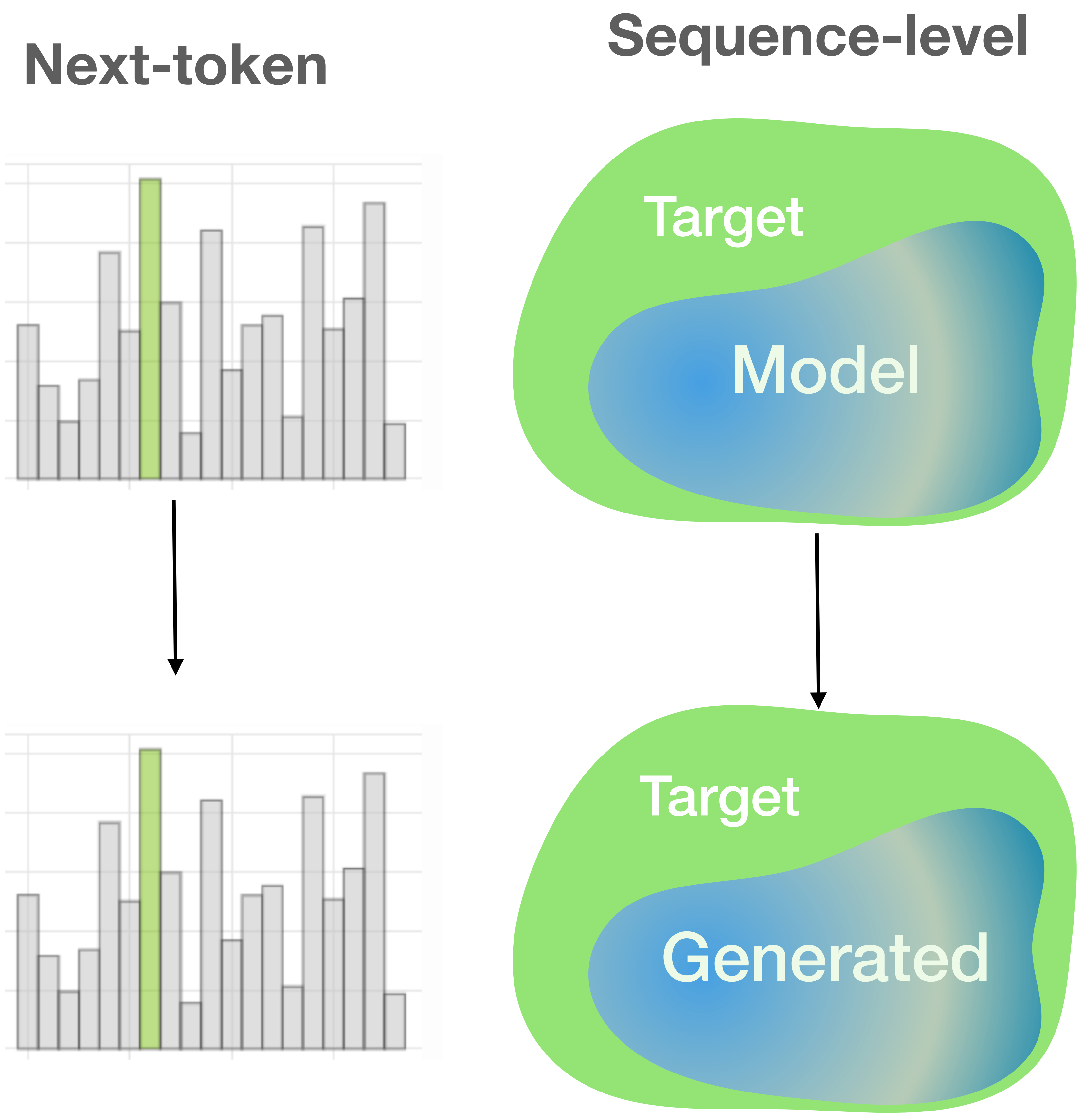
- **Goal**: generate a continuation $\mathbf{y}$ given a model p_θ and prefix $\mathbf{x}$
  - Sampling
    - $\mathbf{y} \sim p_\theta(\cdot \mid \mathbf{x})$
  - Mode-seeking
    - $\mathbf{y} = \arg\max_{\mathbf{y}} p_\theta(\mathbf{y} \mid \mathbf{x})$

Decoding

Building blocks | Decoding

Generating sequences from our model

- **Ancestral sampling:** sample from the model's distribution
    - Until $y_t = \langle end \rangle$:
        - $y_t \sim p_\theta(\cdot \,|\, \mathbf{y}_{<t})$
- $\mathbf{y}$ is a sample from $p_\theta(\mathbf{y})$, since
    - $p_\theta(\mathbf{y}) = \prod_{t=1}^{T} p_\theta(y_t \,|\, \mathbf{y}_{<t})$

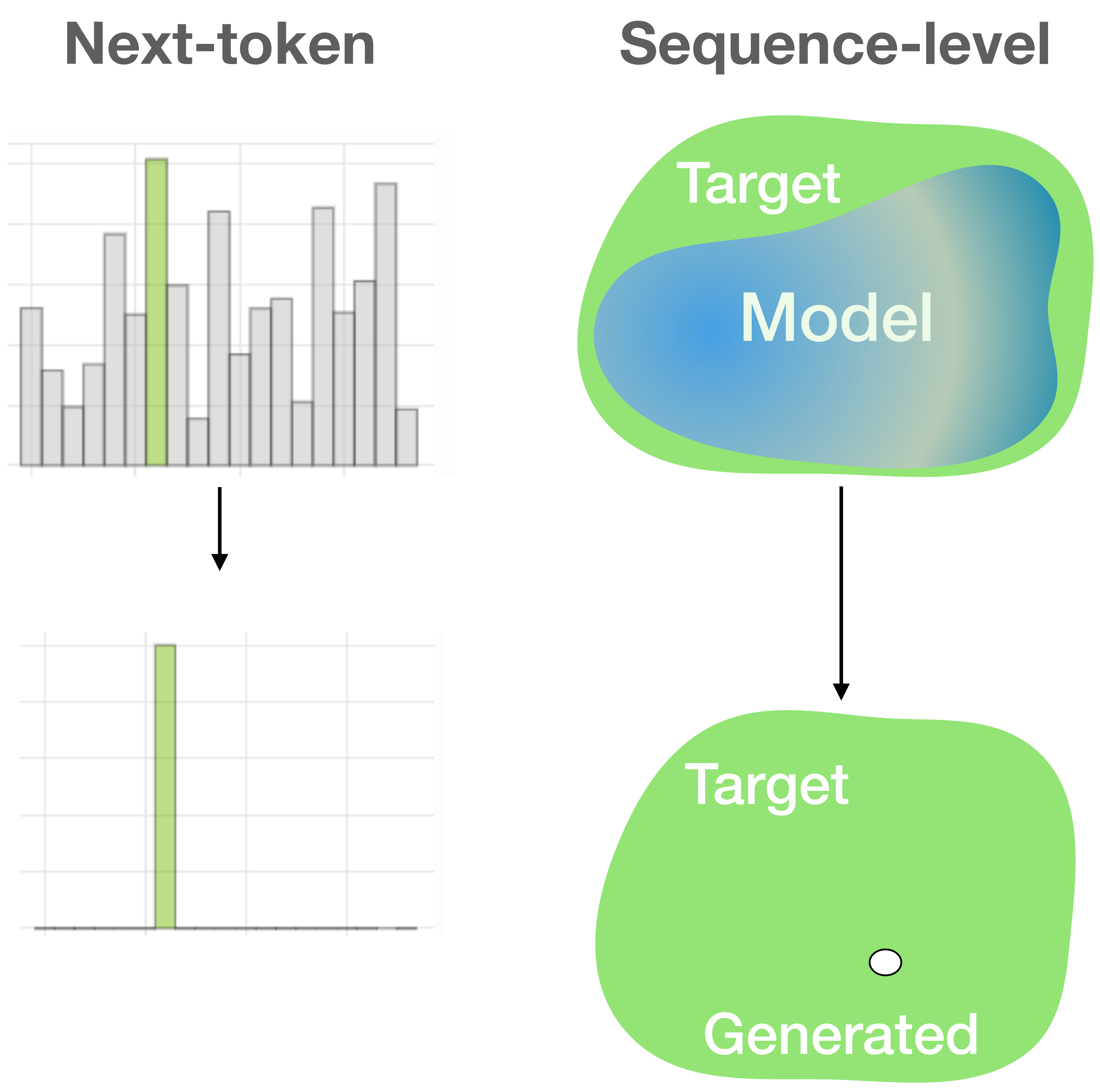


Next-token: https://lena-voita.github.io/nlp_course/language_modeling.html

Building blocks | Decoding

Generating sequences from our model

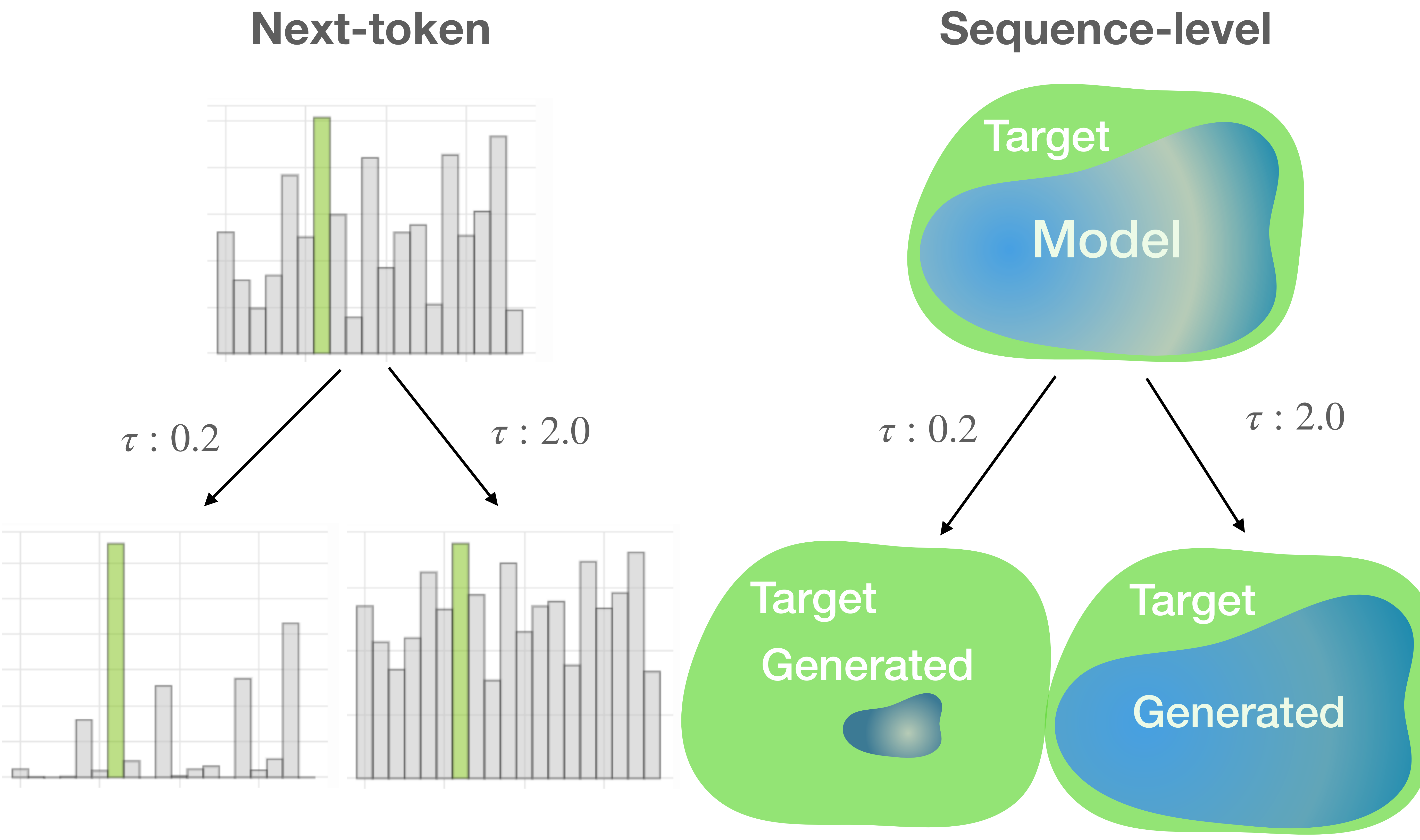
- **Greedy decoding:** select the most-probable token at each step
  - Until $y_t = \langle end \rangle$:
    - $y_t = \arg\max_{y \in V} p_\theta(\cdot \mid \mathbf{y}_{<t}, \mathbf{x})$
- $\mathbf{y}$ is a (naive) approximation of
  - $\arg\max_{\mathbf{y}} p_\theta(\mathbf{y} \mid \mathbf{x})$



Building blocks | Decoding

Generating sequences from our model

- **Temperature Sampling:** adjust each distribution & sample
  - Until $y_t = \langle end \rangle$:
    - $y_t \sim p_\theta^\tau(\cdot \mid \mathbf{y}_{<t})$
  - Where $p_\theta^\tau(\cdot \mid \ldots) = \text{softmax}(s_t/\tau)$, $\tau \in \mathbb{R}_{>0}$
- τ small: "sharpens" the distribution
  - $\tau \to 0$: greedy decoding
- τ big: "flattens" the distribution
  - $\tau \to \infty$: uniform distribution

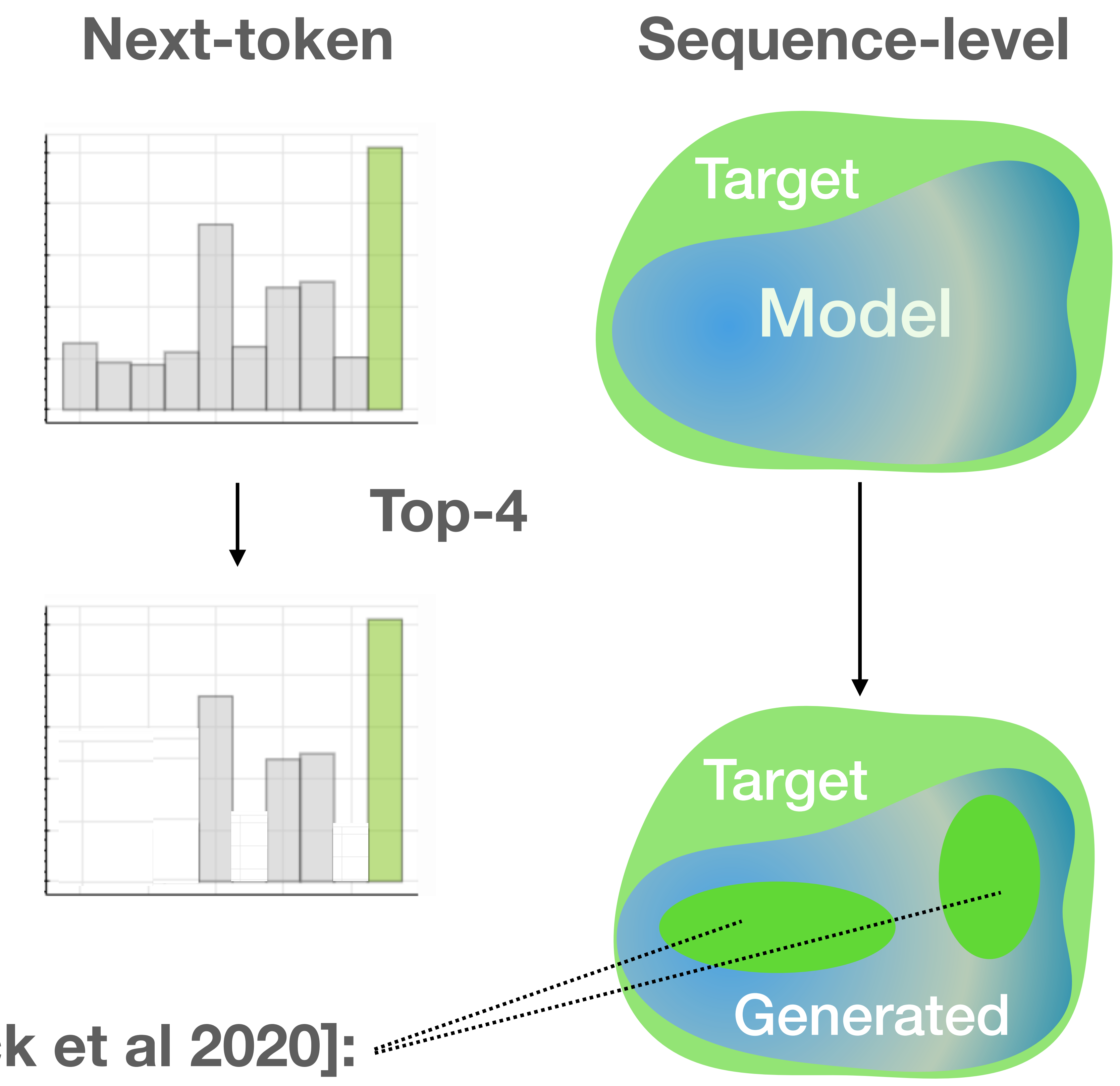


Decoding

Building blocks | Decoding

Generating sequences from our model

- **Top-k sampling:** sample from the k-most-probable tokens
    - $y_t \sim \propto \begin{cases} p_\theta(y \mid \mathbf{y}_{<t}) & y \in \text{top-k} \\ 0 & \text{otherwise} \end{cases}$
- *k* small: only sample from highly-ranked tokens
    - k=1: greedy decoding
    - k=|*V*|: ancestral sampling

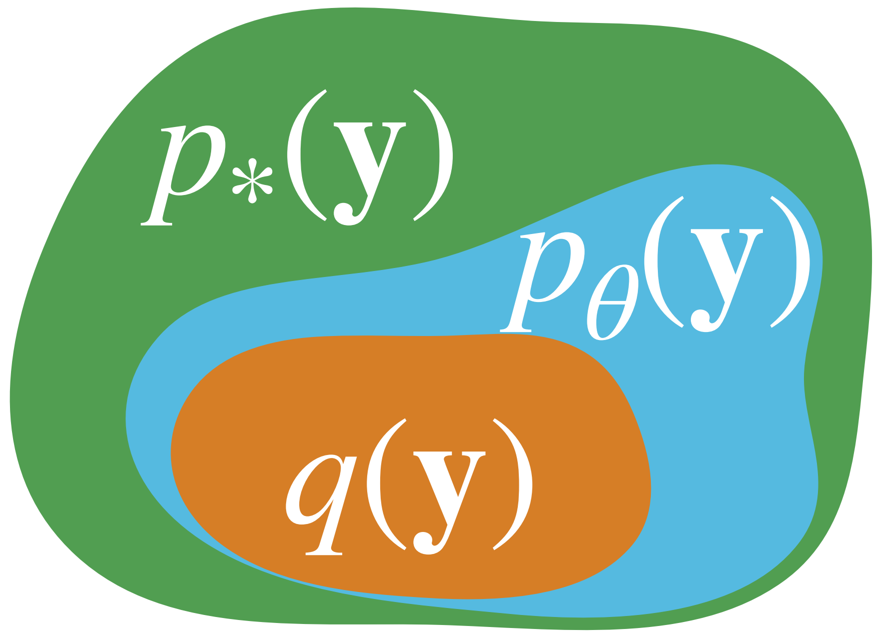


Yes- these holes are problematic, see [Welleck et al 2020]:
[Consistency of a Recurrent Language Model With Respect to Incomplete Decoding]

Building blocks | Decoding

Generating sequences from our model

- What is going on? **Distributional view**
  - Using a decoding algorithm gives us a *new generation distribution* $q(\mathbf{y} \mid p_\theta)$
    - In practice, we do this with new *per-step distributions,* $q^{(t)}(y_t \mid p_\theta, \mathbf{y}_{<t})$.
  - Varying the decoding algorithm varies the generation distribution q.
  - Generating means sampling from q.



Recap

Modeling and generating sequences

- Today's language models consist of three building blocks:
    - An *autoregressive model* that reduces language modeling to classification.
    - *Learning* the model's parameters by maximum likelihood.
    - Generating with a *decoding* algorithm.
- Lab: generate text with a real-world language model.

Looking ahead

Controls & constraints

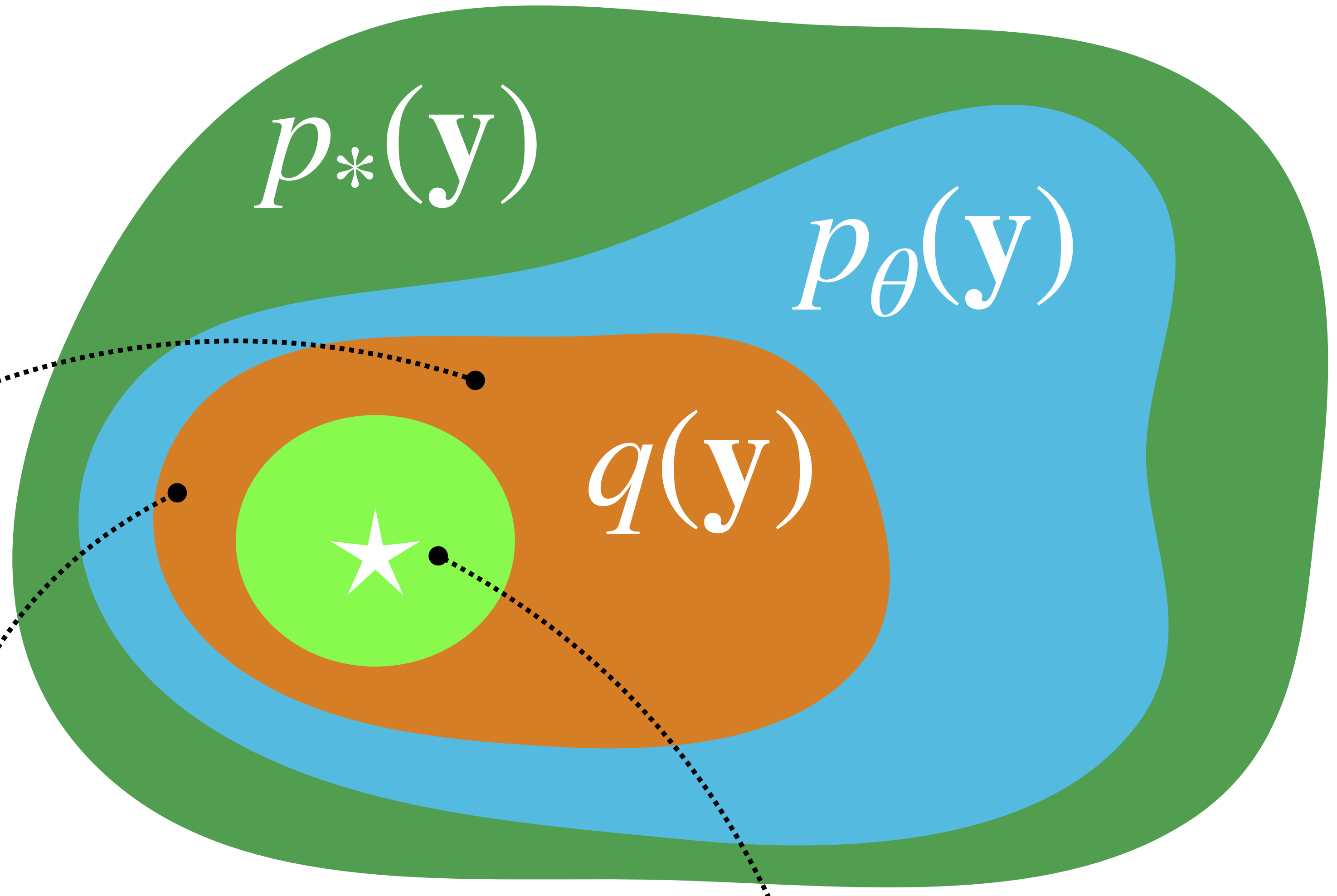
- Generating what the model has learned…
  - *Degeneracies* [e.g. Holtzman et al 2020, Welleck et al 2020]

    MLE: he said . “ We ’re going to crash . We ’re going to crash . We ’re going to crash . We ’re going to crash . We ’re going to crash . We ’re going to crash . We ’re going to crash . We ’re going to …
  - *Logical incoherence* [e.g. Welleck et al 2019, Welleck et al 2021]

    Language Model: I do! I have 2 cats. […later in the conversation…] I don’t have any pets.

    Language Model: By the definition of odd number, x = 2k for some integer k.
  - *Toxicity, bias* [e.g. Gehman et al 2020]

    Language Model: Hi how are you doing? I think you are #@$&*@.



- … vs. generating what we want

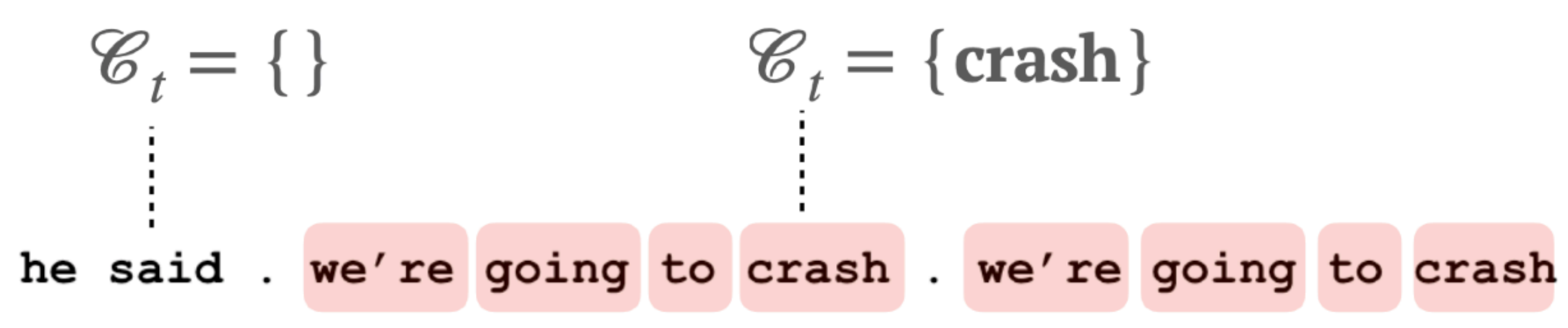
  Unlikelihood: Hood said . “ I ’m going to make sure we ’re going to get back to the water . ” The order to abandon ship was given by Admiral Beatty , who ordered the remaining two battlecruisers to turn away . At 18 : 25 , Hood turned his..

  Neural Text Generation with Unlikelihood Training

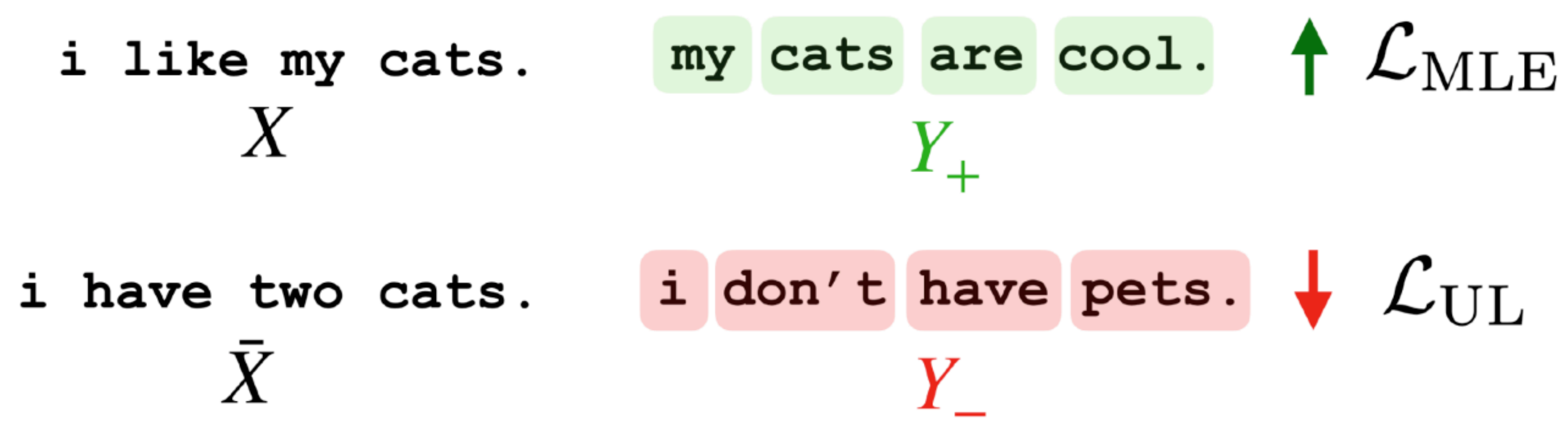
Looking ahead

Controls & constraints

- Constraints through *learning what not to do*

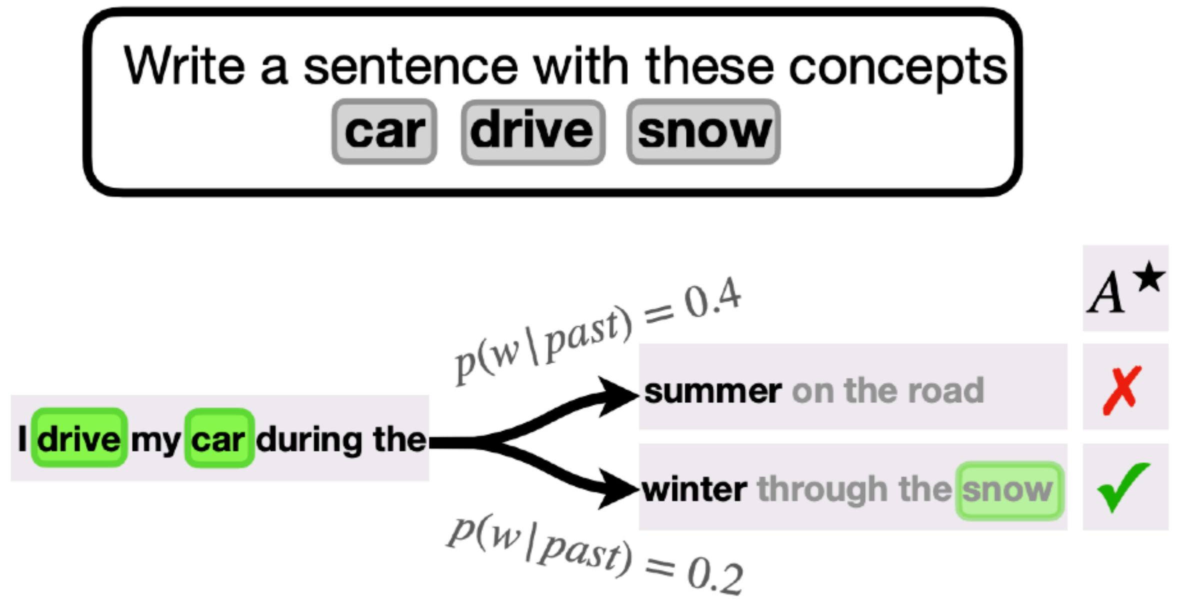


Neural Text Generation with Unlikelihood Training

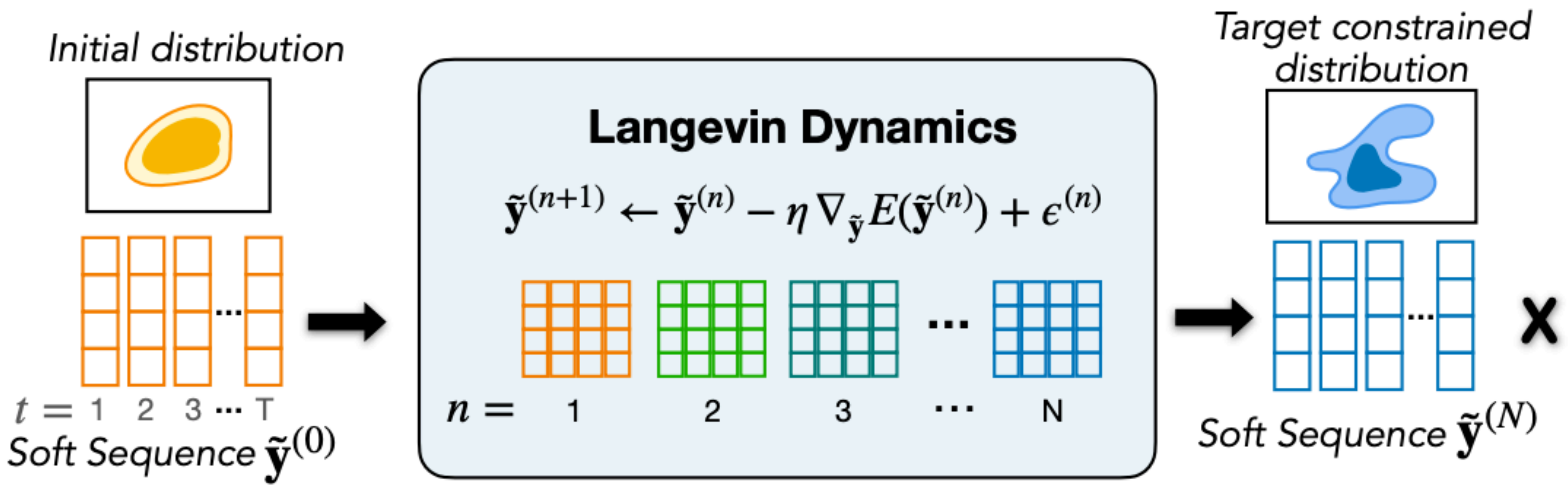


Making Inconsistent Dialogue Unlikely with Unlikelihood Training

- Constraints through *inference*



Constrained Text Generation with Lookahead Heuristics



Energy-based Constrained Text Generation with Langevin Dynamics

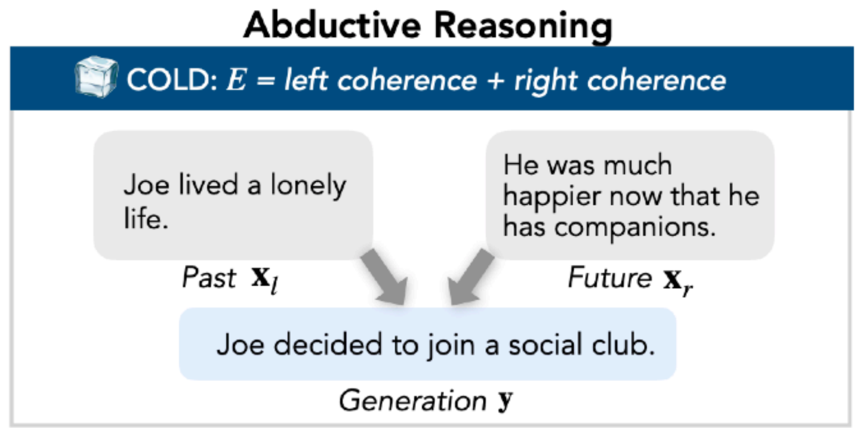
Looking ahead

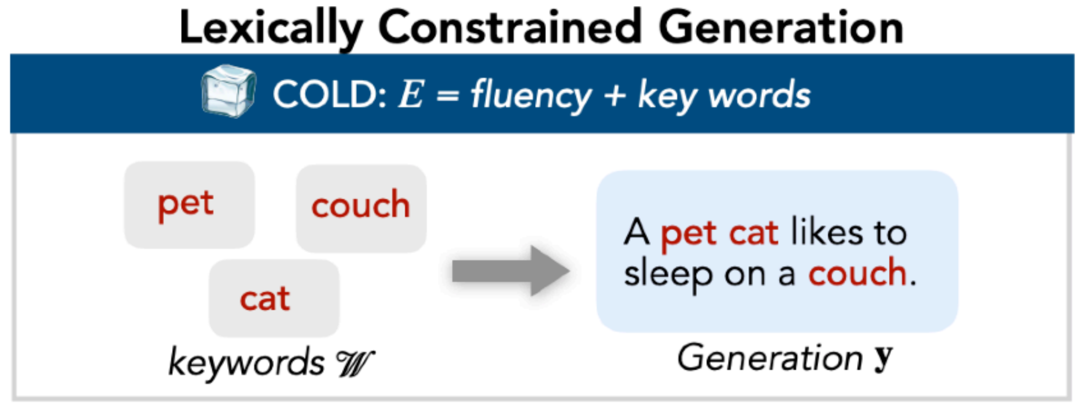
- Align with human values & expectations

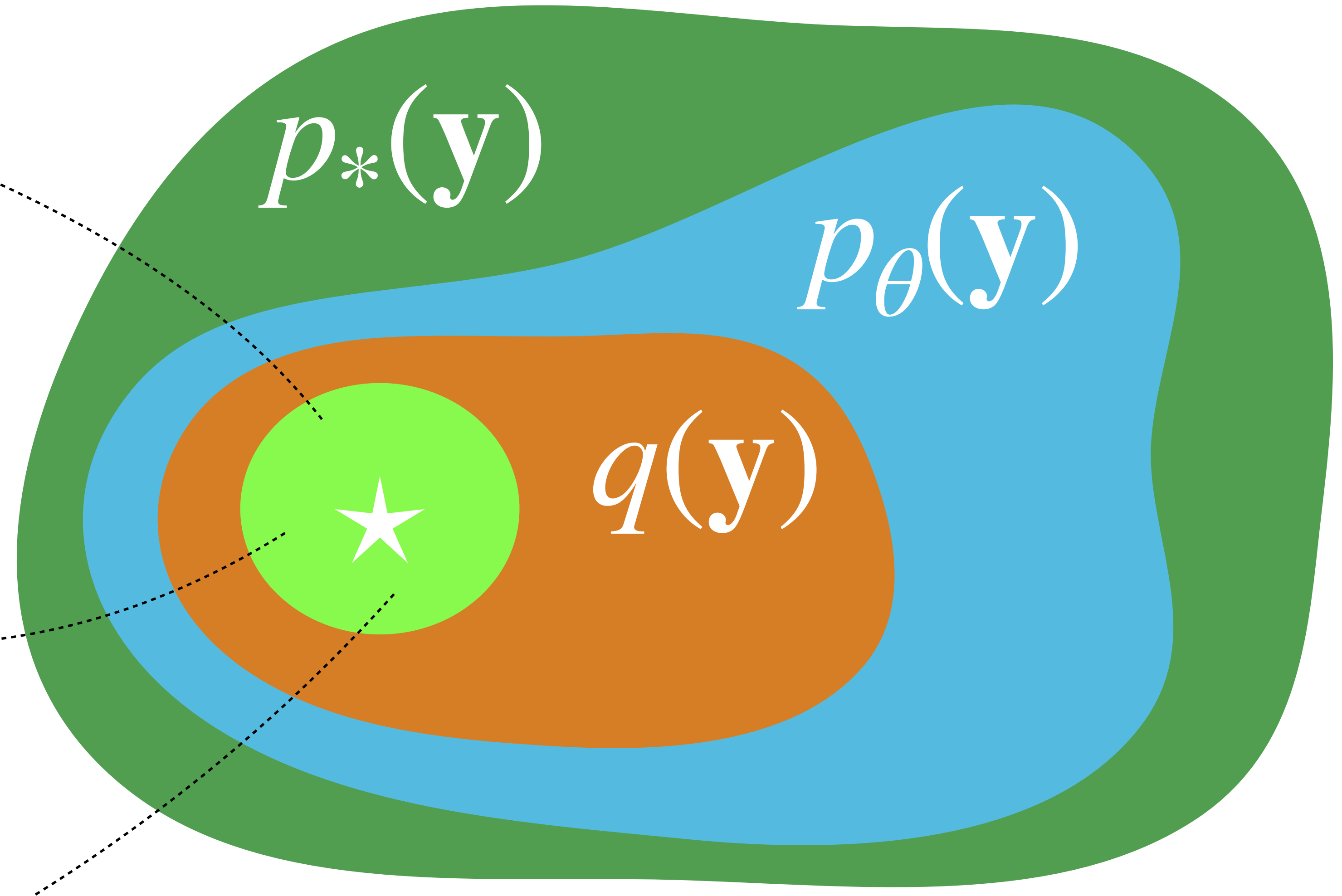
MLE: he said . “ We ’re going to crash . We ’re going to crash . We ’re going to crash . We ’re going to crash . We ’re going to crash . We ’re going to crash . We ’re going to crash . We ’re going to …

Unlikelihood: Hood said . “ I ’m going to make sure we ’re going to get back to the water . ” The order to abandon ship was given by Admiral Beatty , who ordered the remaining two battlecruisers to turn away . At 18 : 25 , Hood turned his..

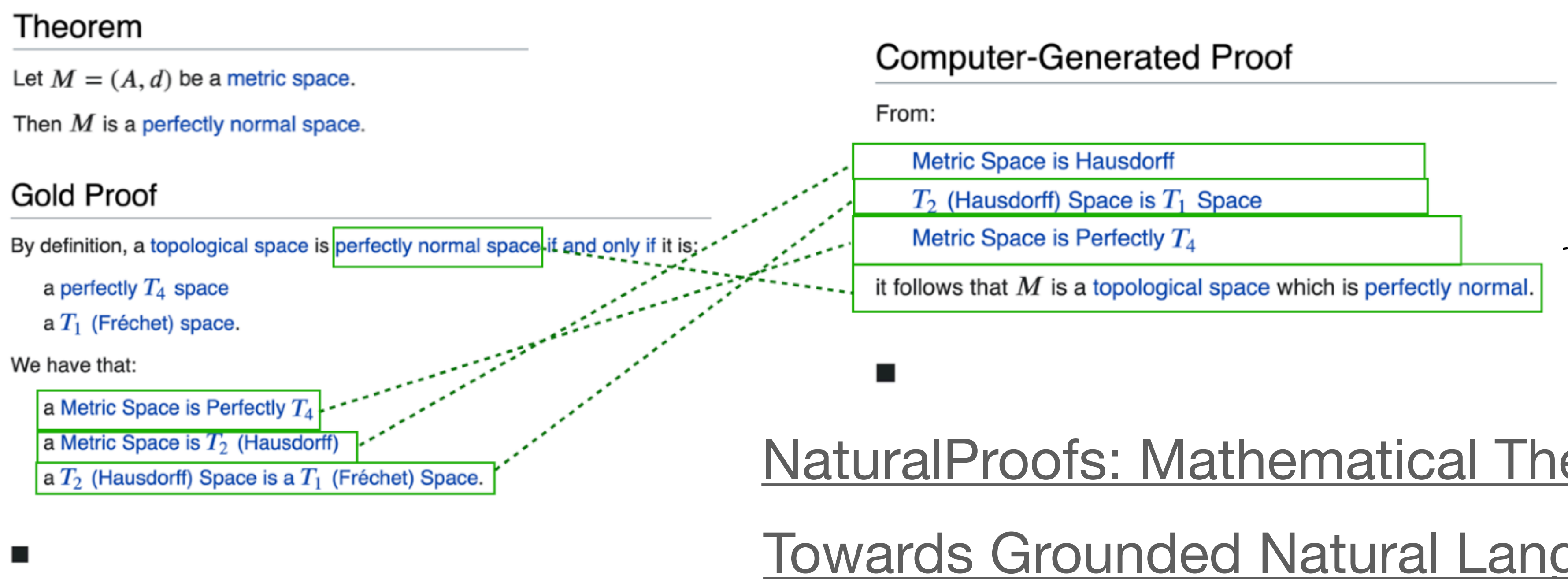
- Flexibly adapt to new settings







- Enable long-term coherence and deeper reasoning



NaturalProofs: Mathematical Theorem Proving in Natural Language

Towards Grounded Natural Language Proof Generation (Work in Progress)

Thanks for your attention!