Carnegie Mellon University

## Does exposure bias really matter?

Let's look for its impact on neural text degeneration!

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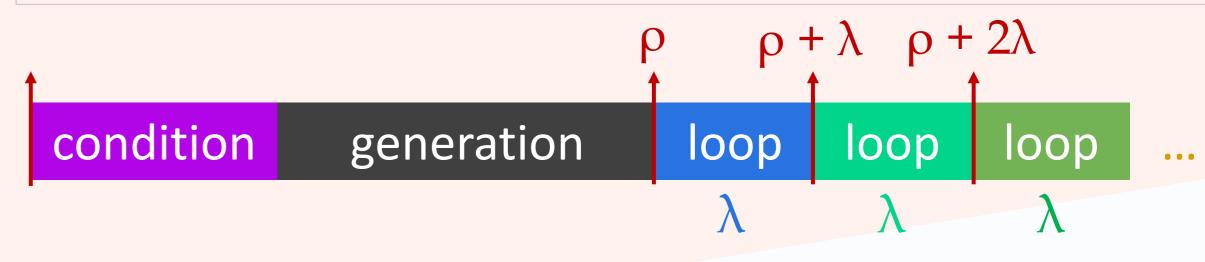
Relating Neural Text Degeneration to Exposure Bias

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## **Neural Text Degeneration**

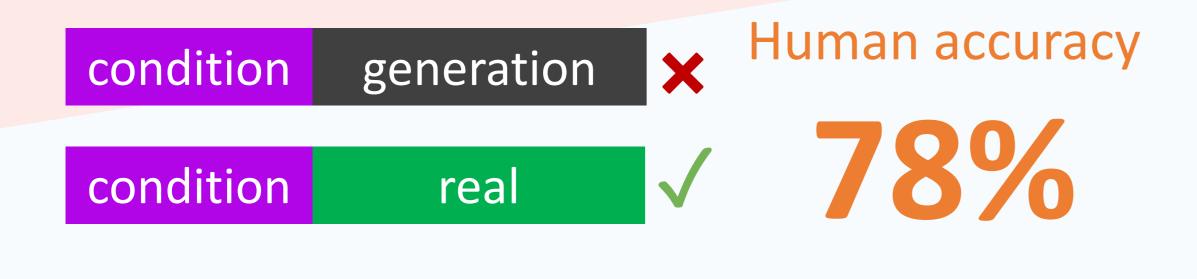
With greedy decoding, GPT-2 just repeats...

We first saw Anki Overdrive, the company's follow-up to the original game, in the early 2000s. It was a game that was a bit of a hit, and it was a game **that was a bit of a hit that was a** bit of a hit that was a bit of a



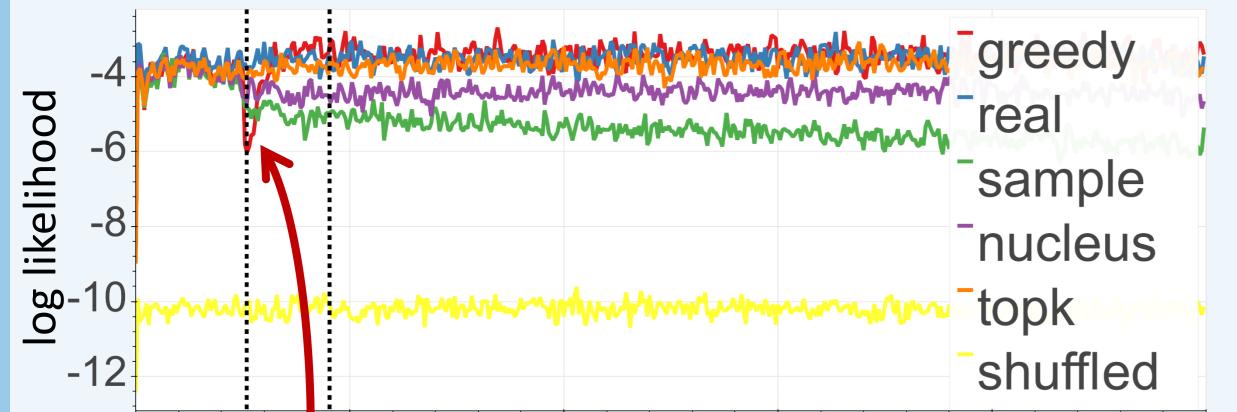
## Mistakes are made in the early phase

## 1. Qualitatively: classify real / artificial.



conditiongenerationlooploopImplication: This part is unnatural.

## 2. Quantitatively: estimate likelihood with MLM



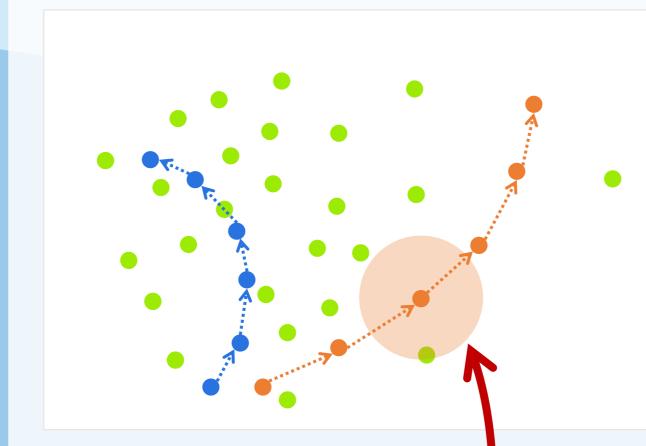
#### **Indications of Exposure Bias**

#### 1. Mistakes are made in the early phase

- Qualitatively: unnatural text.
- Quantitively: low likelihood.
- 2. Mistakes are significant to the model
  - lead the model to a state unseen in training time

# Mistakes are significant to the model

## **Compare the states to real states:**



Real states:
generated by
encoding real text.

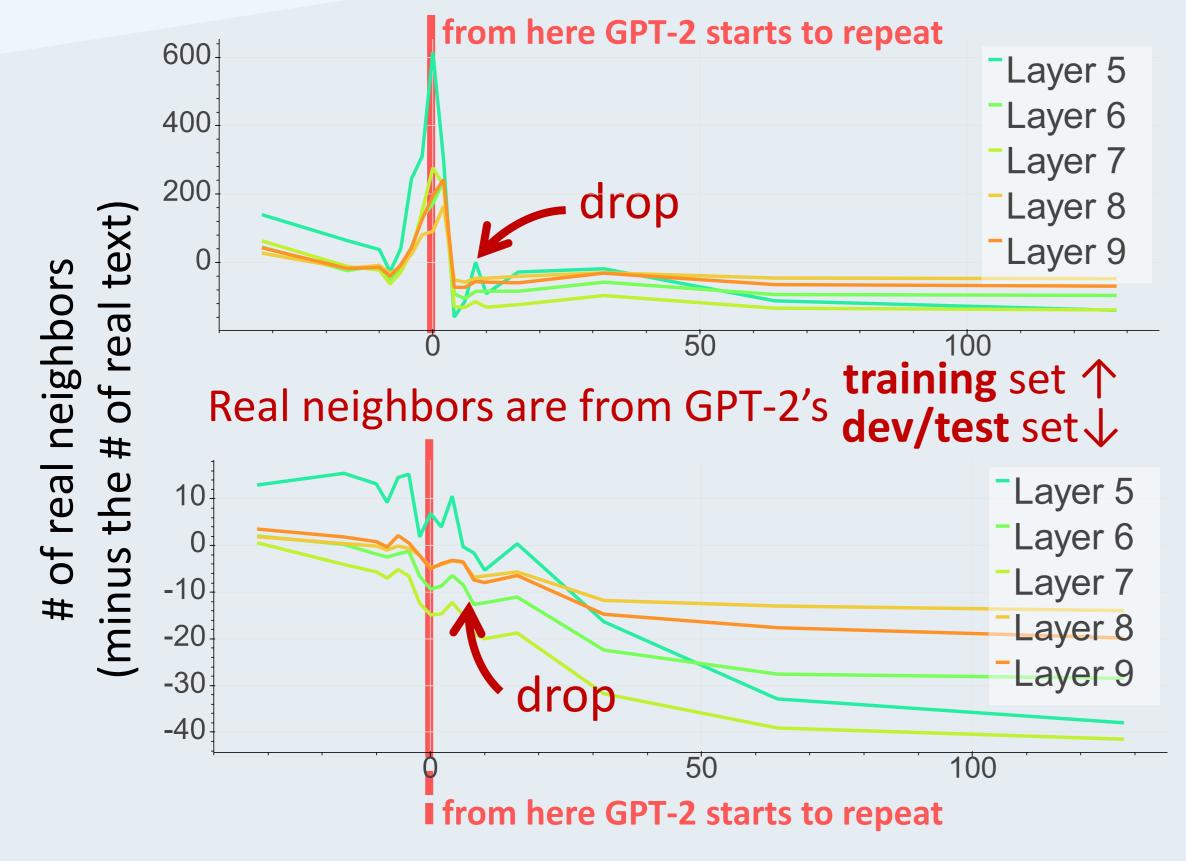
Artificial states: states
of a generated
sentence.

0 100 200 300 400 500 token position A sharp drop at the beginning of generation.

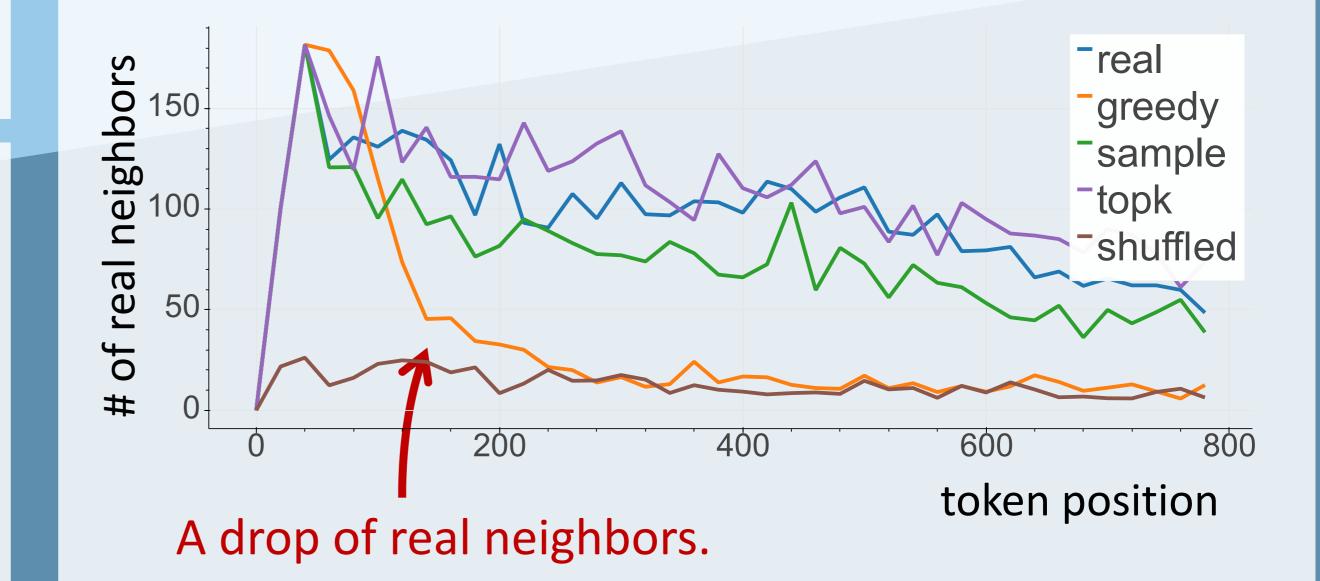
Indication: Mistakes are made at the beginning.

## A Closer Look at the # of Neighbors

x-axis: token position relative to  $\rho + \lambda$ 



#### Count the number of real neighbors.



Indication: Mistakes are significant to the model.

## Takeaways

- 1. We summarize the indications of exposure bias.
- 2. We design the associated experiments.
- 3. Our results indicate the relation between

#### exposure bias and neural text degeneration.