

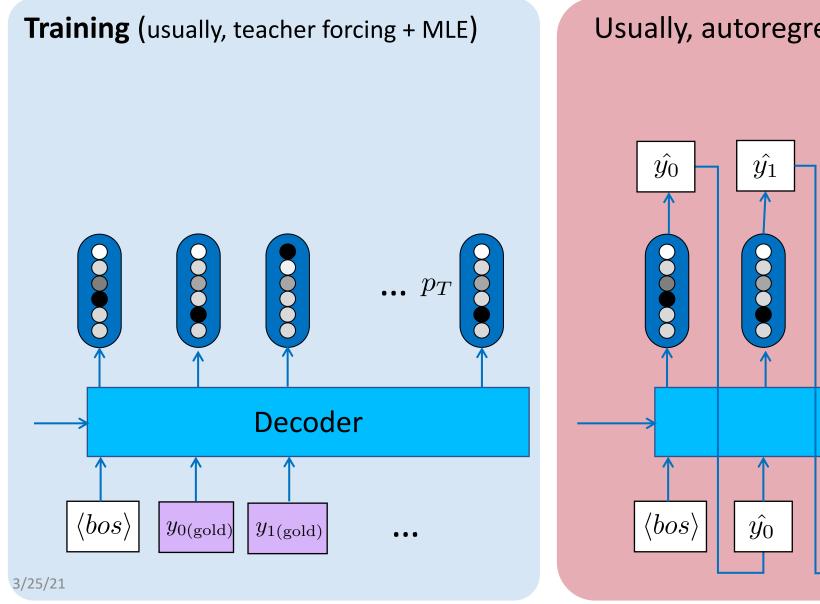
# Text Generation by Learning from Demonstrations

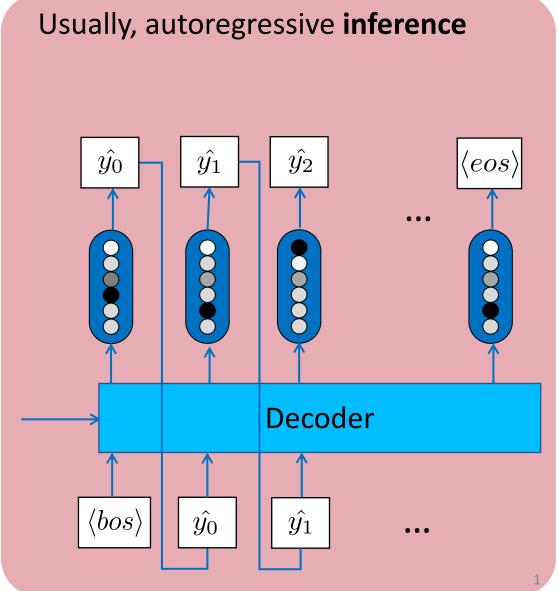
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The most widespread approach for supervised conditional text generation:





### Motivation 1: mismatched history (gold vs. model-generated)

#### Beam Search, b=32, from GPT-2:

Repetition

Hallucination

"The study, published in the Proceedings of the National Academy of Sciences of the United States of America (PNAS), was conducted by researchers from the Universidad Nacional Autónoma de México (UNAM) and the Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de II., 2020)

Machine translation hallucination (Wang and Sennrich, 2020):

Source: So höre nicht auf die Ableugner.

Reference: So hearken not to those who deny.

MLE: Do not drive or use machines.

## Motivation 2: mismatched learning/evaluation objectives

$$\mathbb{E}_{oldsymbol{y} \sim p_{ ext{human}}} \sum_{t=0}^{T} \log p_{ heta}(y_t \mid oldsymbol{y}_{0:t-1}, oldsymbol{x})$$

• High recall:  $p_{\vartheta}$  must cover all outputs from  $p_{\mathsf{human}}$ 

$$\mathbb{E}_{\boldsymbol{y} \sim p_{\theta}} \sum_{t=0}^{T} \log p_{\text{human}}(y_t \mid \boldsymbol{y}_{0:t-1}, \boldsymbol{x})$$

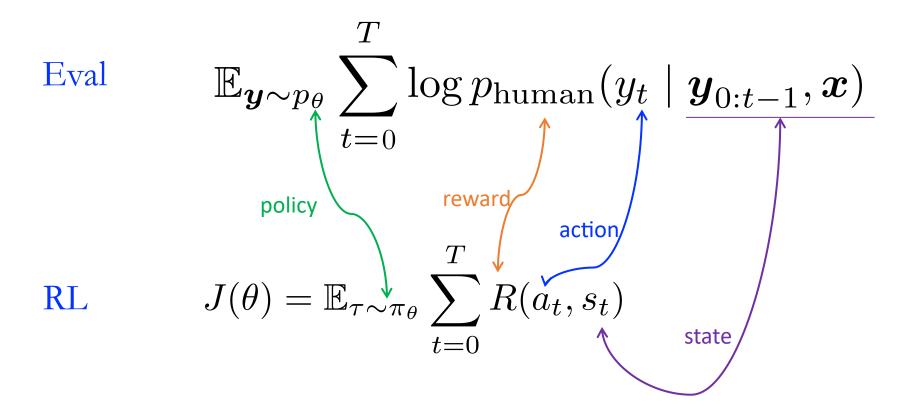
• High **precision**: all outputs from  $p_{\vartheta}$  must be scored high under  $p_{\text{human}}$ 

## Motivation

→ Background: RL formulation of text gen
Offline objective: learning algorithm GOLD

# Background: RL in text generation

$$\underbrace{\mathsf{MLE}} \qquad \mathbb{E}_{\boldsymbol{y} \sim p_{\mathrm{human}}} \sum_{t=0}^{T} \log p_{\theta}(y_t \mid \boldsymbol{y}_{0:t-1}, \boldsymbol{x})$$



# Background: RL in text generation

- Prior approach: directly optimize a sequence-level metric like BLEU, ROUGE, etc., using policy gradient
  - Pros: no exposure bias; may discover high-quality outputs outside the references
  - Cons: degenerate solutions and difficult optimization (gradient estimated by samples from policy has high variance)

$$J( heta) = \mathbb{E}_{ au \sim \pi_{ heta}}^{ ext{policy}} \sum_{t=0}^{T} \stackrel{ ext{action}}{R(a_t, s_t)}$$
state

## Motivation

Background: RL formulation of text gen

→ Offline objective: learning algorithm GOLD

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## Online vs. offline policy gradient

#### Online + on-policy policy gradient

- Step 1: sample outputs from the model
- Step 2: get seq-level rewards like BLEU
- Step 3: use policy gradient to optimize

$$\nabla_{\theta} J(\theta) = \mathbb{E}_{\tau \sim \mathbf{p}_{\theta}} \sum_{t} \nabla_{\theta} \log \pi_{\theta}(a_{t} \mid s_{t}) \hat{Q}(s_{t}, a_{t})$$

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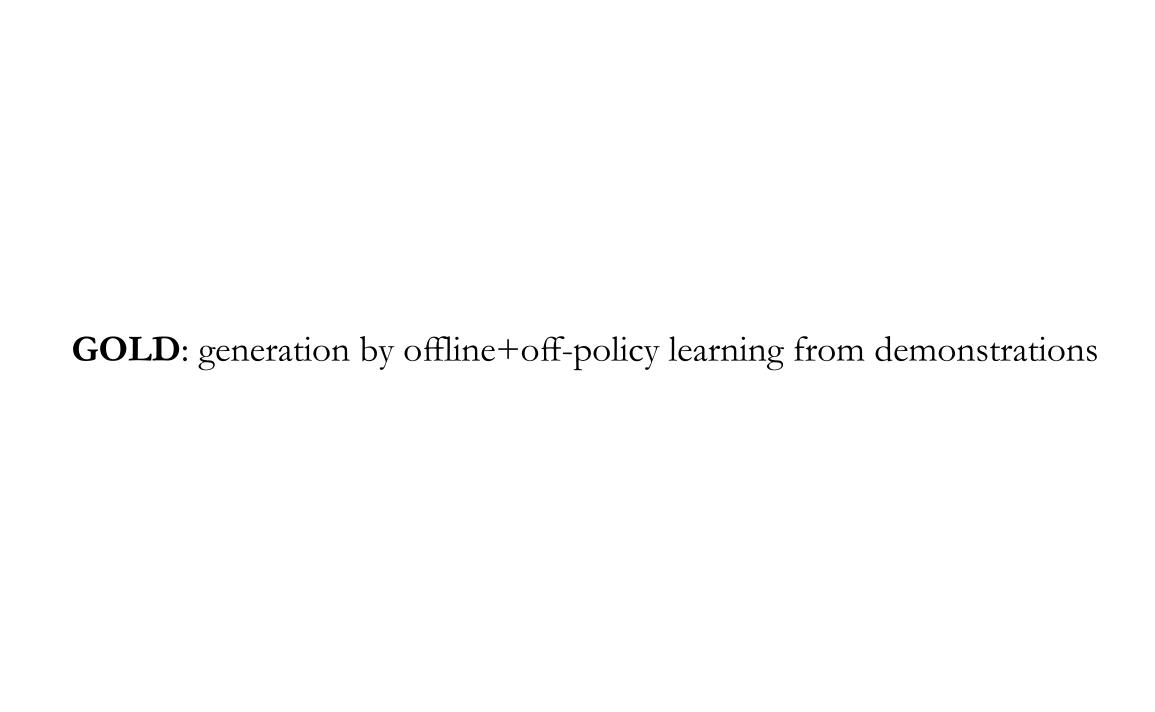
# No interaction with the environment Offline + off-policy policy gradient

- Step 1: sample from demonstrations (i.e., gold supervised data)
- Step 2: get token-level rewards based on  $p_{\rm MLE}$
- Step 3: use policy gradient to optimize

$$egin{aligned} 
abla_{ heta} J( heta) &= \mathbb{E}_{ au \sim \pi_b} \sum_t w_t 
abla_{ heta} \log \pi_{ heta}(a_t \mid s_t) \hat{Q}(s_t, a_t) \ \pi_b &= p_{ ext{human}} & w_t pprox \pi_{ heta}(a_{t'} \mid s_{t'}) & \hat{Q}(s_t, a_t) &= \sum_{t' = t}^T \gamma^{t' - t} r_{t'} \end{aligned}$$
 use empirical distin model confidence  $p_{ ext{MLE}}$  based reward (see paper)

#### <u>Intuition</u>

- Upweight more "confident" examples; focus more on successful data (closer to test-time distribution)
- Intuitively reduce exposure bias



#### Input

#### Output

NQG (using SQuAD)

The College of the University of Chicago grants Bachelor of Arts and Bachelor of Science degrees in 50 academic majors and 28 minors

How many academic minors does the university grant in total?

CNN/DailyMail (extractive summarization)

Actor Wince Vaught and top op that Lady Gog mastered up the courage to dive into feecing cold vature for the Special Olympic charges; the day after cities across the counter books cold records for the most "The Chicoperative Weelding Crashers star we the coldering paces of born or als his homeworks small Dollon Plung, in which brave commences are considered to the plung into I also Medingon. Vaught, wearing a Blackhawds hockey irrey and jeans, led the way into a patte of frigid, shally 33 degree water near Lincol Park that had been cleared of snow, which has accommodated in the city and much of the US. Second I down for videous (1), edg. Acros Weel Vaught was the Sepecial Olympic belong eclosiving seat on Studies, which was accommodated in the city and much of the US. Second I down for videous Consideration, which was a commodated in the city and waterned up with a towel after the prince of the Carlon of the Consideration of the Considerati

Chicago-native Vaughn was celebrity guest at his hometown's annual Polar Plunge for Special Olympics . Newly-engaged Lady Gaga attended with Chicago Fire fiance Taylor Kinney and his television co-stars . City tied 140-year record for coldest February with 14.6 degree average and more winter weather expected across US . Winter Storm Sparta brings more snow and ice to East Coast after causing tragic weather-related deaths in Midwest . Boston can possibly eclipse its record for most snow in one winter if it receives 5.7 more inches .

XSum (abstractive summarization)

The country's consumer watchdog has taken Apple to court for false advertising because the tablet computer does not work on Australia's 4G network. Apple's lawyers said they were willing to publish a clarification. However the company does not accept that it misled customers. The Australian Competition and Consumer Commission (ACCC) said on Tuesday: "Apple's recent promotion of the new 'iPad with wi-fi + 4G' is misleading because it represents to Australian consumers that the product can, with a sim card, connect to a 4G mobile data network in Australia, when this is not the case." The watchdog then lodged a complaint at the Federal Court in Melbourne. At a preliminary hearing, Apple lawyer Paul Anastassiou said Apple had never claimed the device would work fully on the current 4G network operated by Telstra. Apple says the new iPad works on what is globally accepted to be a 4G network. The matter will go to a full trial on 2 May. The Apple iPad's third version went on sale earlier this month, with Australia the first country where it was available. Shoppers lined up by the hundreds at Apple stores on opening day and the company said it had been its strongest iPad launch to date. The ACCC said it was seeking an injunction on sales as well as a financial penalty against Apple, corrective advertising and refunds to consumers. On its website, Apple does state that 4G LTE is only supported on selected networks in the US and Canada.

US technology firm Apple has offered to refund Australian customers who felt misled about the 4G capabilities of the new iPad.

IWLST14 De-En (machine translation)

Im amerikanischen mittelwesten luden bauern getreide auf kähne und sandten es den fluss hoch auf den markt nach chicago .

In the American midwest, farmers used to load grain onto barges and send it upriver to the chicago market.

## Our hypotheses to **GOLD**

#### 1. GOLD improves generation quality

• Automatic results

Accordance resorts	NQG (BART) (BLEU)	CNN/DM (BART) (R-2)	XSum (BART) (R-2)	IWSLT14 De-En (Transformer) (BLEU)
MLE	20.68	21.28	22.08	34.64
GOLD-p (product as Q)	21.42	22.01	22.26	35.33
GOLD-s (sum as Q)	21.98	22.09	22.58	35.45

• Human evals: pairwise comparison of GOLD-s vs. MLE generations

#### 2. GOLD improves precision at the cost of recall

- High precision: larger BLEU/ROUGE, better human evals
- Low recall: very large perplexity w.r.t. gold standards

High perplexity != low quality

#### 3. GOLD alleviates exposure bias

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## Takeaways

- 1. MLE encourages high recall
- 2. GOLD (generation by off-policy and offline learning from demonstration) is easy to implement and optimize
  - Essentially weighted MLE
- 3. GOLD encourages high-precision generation
  - Instead of distribution matching

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