KOREA UNIVERSITY

DSBA CS224n 2021 Study

[Lecture 12]
Natural Language Generation

DSBA
Data Science & Business Analytics

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00 발표 목차
Contents

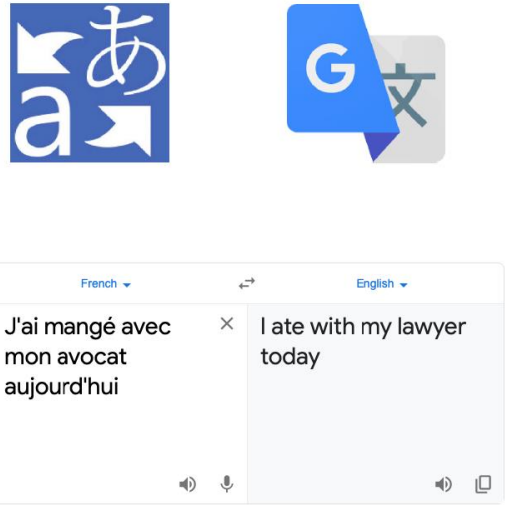
01 What is NLG

Natural Language Generation

What is natural language generation

- NLG 는 자연어처리(NLP)의 한 분야
- Machine Translation, Dialogue System, Summarization, Data-to-Text Generation, Visual Description

<Machine Translation>



<Summarization>

C: Looking at what we've got, we we want an LCD display with a spinning wheel.
B: You have to have some push-buttons, don't you?
C: Just spinning and not scrolling, I would say.
B: I think the spinning wheel is definitely very now.
A: but since LCDs seems to be uh a definite yes,
C: We're having push-buttons on the outside
C: and then on the inside an LCD with spinning wheel,

Decision Abstract (Summary):
The remote will have push buttons outside, and an LCD and spinning wheel inside.

A: and um I'm not sure about the buttons being in the shape of fruit though.
D: Maybe make it like fruity colours or something.
C: The power button could be like a big apple or something.
D: Um like I'm just thinking bright colours.

Problem Abstract (Summary):
How to incorporate a fruit and vegetable theme into the remote.

(Wang and Cardie, ACL 2013)

<Data-to-Text Generation>

TEAM	WIN	LOSS	PTS	FG_PCT	RB	AS ...
Heat	11	12	103	49	47	27
Hawks	7	15	95	43	33	20

PLAYER	AS	RB	PT	FG	FGA	CITY ...
Tyler Johnson	5	2	27	8	16	Miami
Dwight Howard	4	17	23	9	11	Atlanta
Paul Millsap	2	9	21	8	12	Atlanta
Goran Dragic	4	2	21	8	17	Miami
Wayne Ellington	2	3	19	7	15	Miami
Dennis Schroder	7	4	17	8	15	Atlanta
Rodney McGruder	5	5	11	3	8	Miami
Thabo Sefolosha	5	5	10	5	11	Atlanta
Kyle Korver	5	3	9	3	9	Atlanta
...						

The Atlanta Hawks defeated the Miami Heat , 103 - 95 , at Philips Arena on Wednesday . Atlanta was in desperate need of a win and they were able to take care of a shorthanded Miami team here . Defense was key for the Hawks , as they held the Heat to 42 percent shooting and forced them to commit 16 turnovers . Atlanta also dominated in the paint , winning the rebounding battle , 47 - 34 , and outscoring them in the paint 58 - 26.The Hawks shot 49 percent from the field and assisted on 27 of their 43 made baskets . This was a near wire - to - wire win for the Hawks , as Miami held just one lead in the first five minutes . Miami (7 - 15) are as beat - up as anyone right now and it 's taking a toll on the heavily used starters . Hassan Whiteside really struggled in this game , as he amassed eight points , 12 rebounds and one blocks on 4 - of - 12 shooting ...

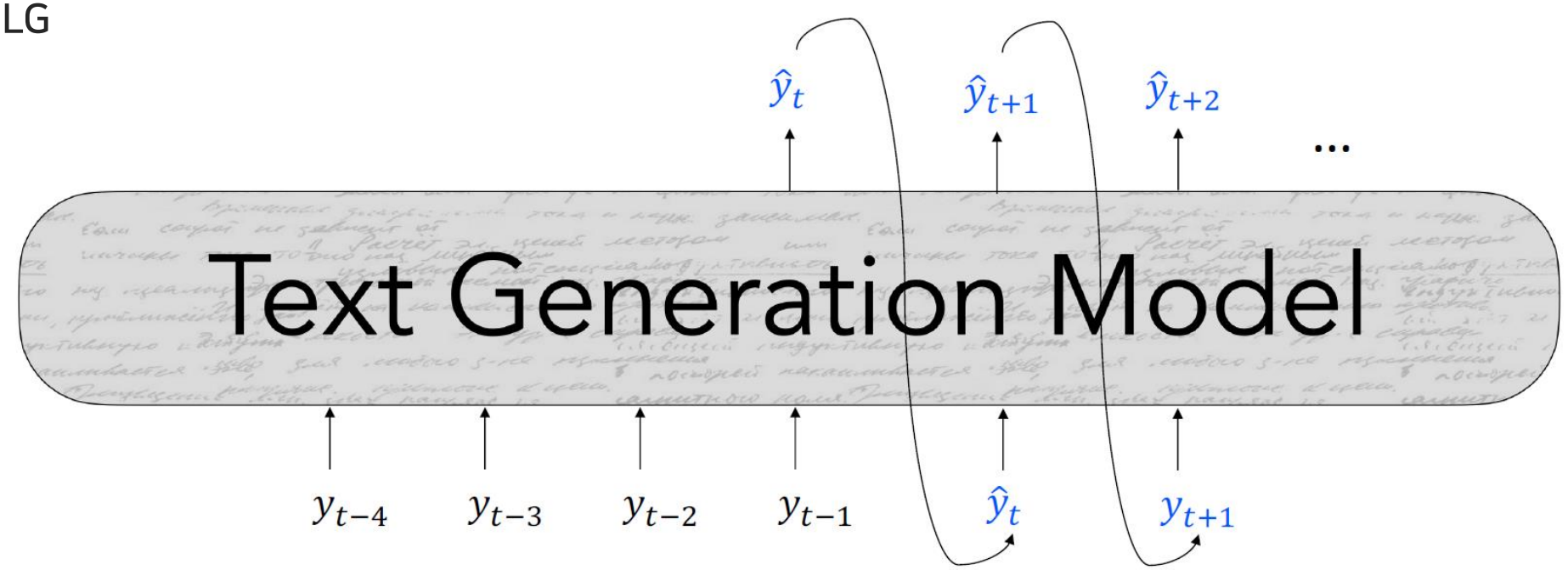
(Wiseman and Rush., EMNLP 2017)

- 사람의 편의를 위해 text 를 생성하는 모든 업무는 NLG 사용가능

01 What is NLG

Formalizing

Basic NLG

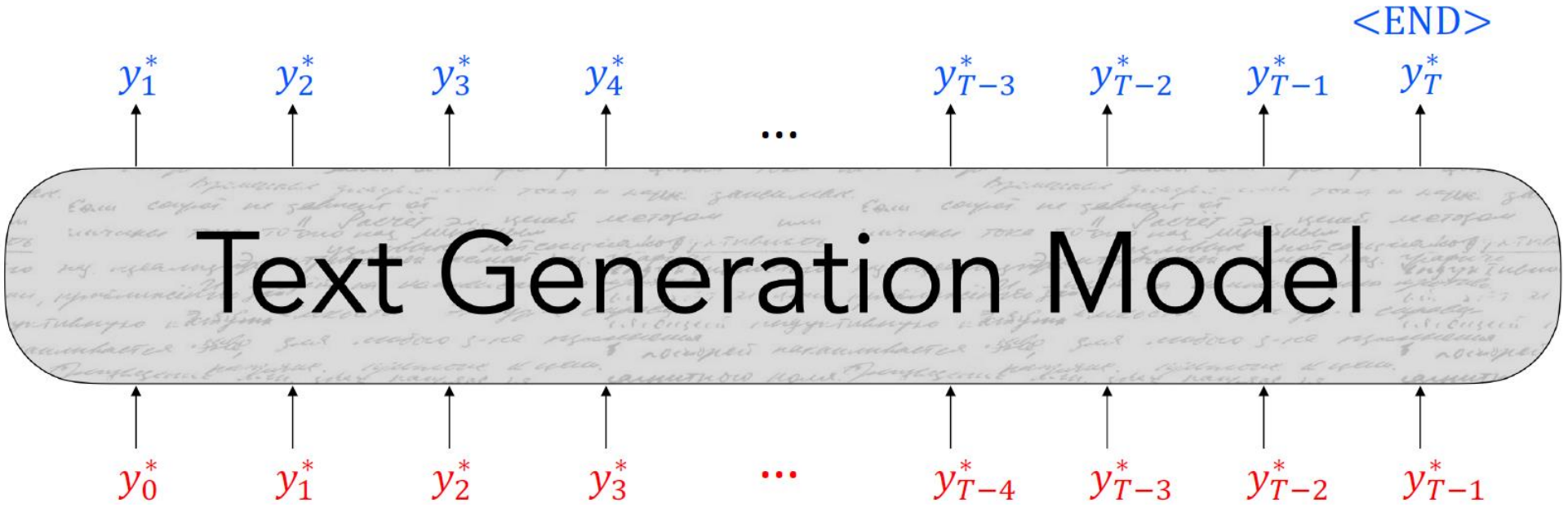


- Autoregressive 형태의 일반적인 NLG 모델은 이전까지의 단어 $\{y\}_{<t}$ 를 입력으로 다음 스텝의 단어 $\hat{y}_t$ 를 생성함
- 학습시엔 예측된 토큰과 실제 토큰을 사용한 Negative loglikelihood 를 minimize 하는 방식을 사용

01 What is NLG

Formalizing

Teacher forcing



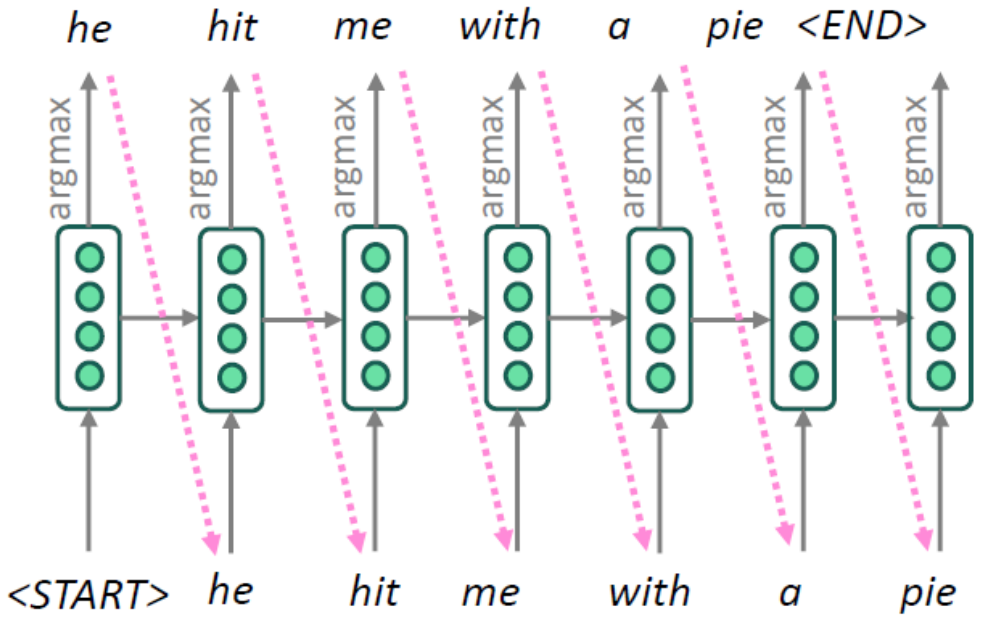
- 학습 시 모델이 예측한 토큰이 아닌 실제 문장의 토큰을 다음 단어 생성을 위한 입력으로 사용할 수 있음
- 초기에 잘못 생성된 단어로 인해 이 후 계속 잘못된 단어가 생성되는 것을 막아줌
- Decoding 시엔 예측된 단어를 다음 단어 예측을 위한 입력으로 사용

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(y_t^* | \{y^*\}_{<t})$$

02 Decoding

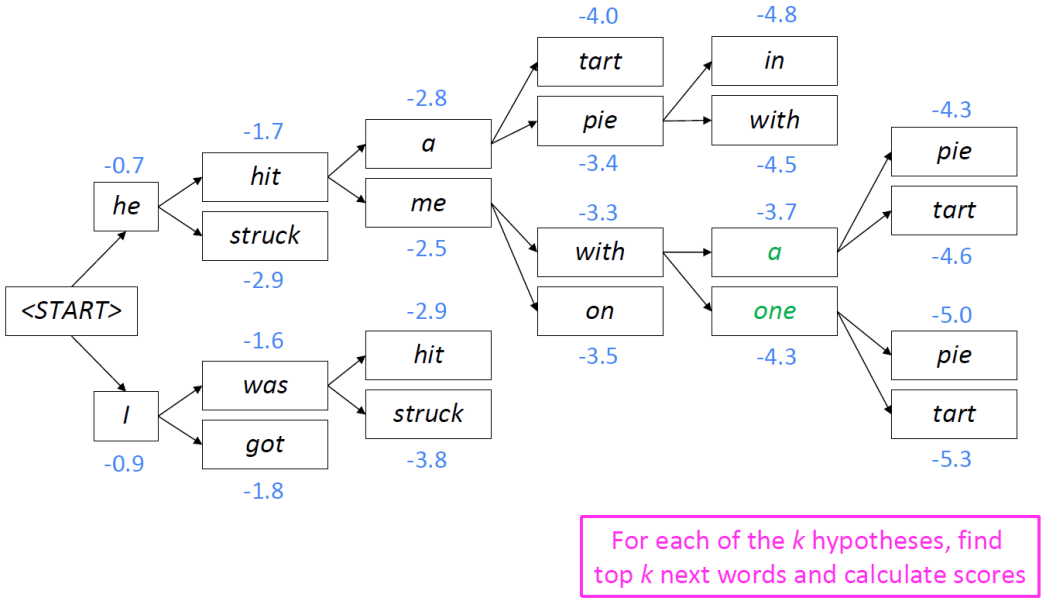
Greedy Methods

Argmax Decoding



- 매 step 마다 vocab 내의 단어 중 probability 가 최대가 되는 단어를 선택

Beam Search



- Argmax decoding 보다 좀 더 많은(k) 후보들을 비교

02 Decoding

Greedy Methods

Greedy methods get repetitive

Context: In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

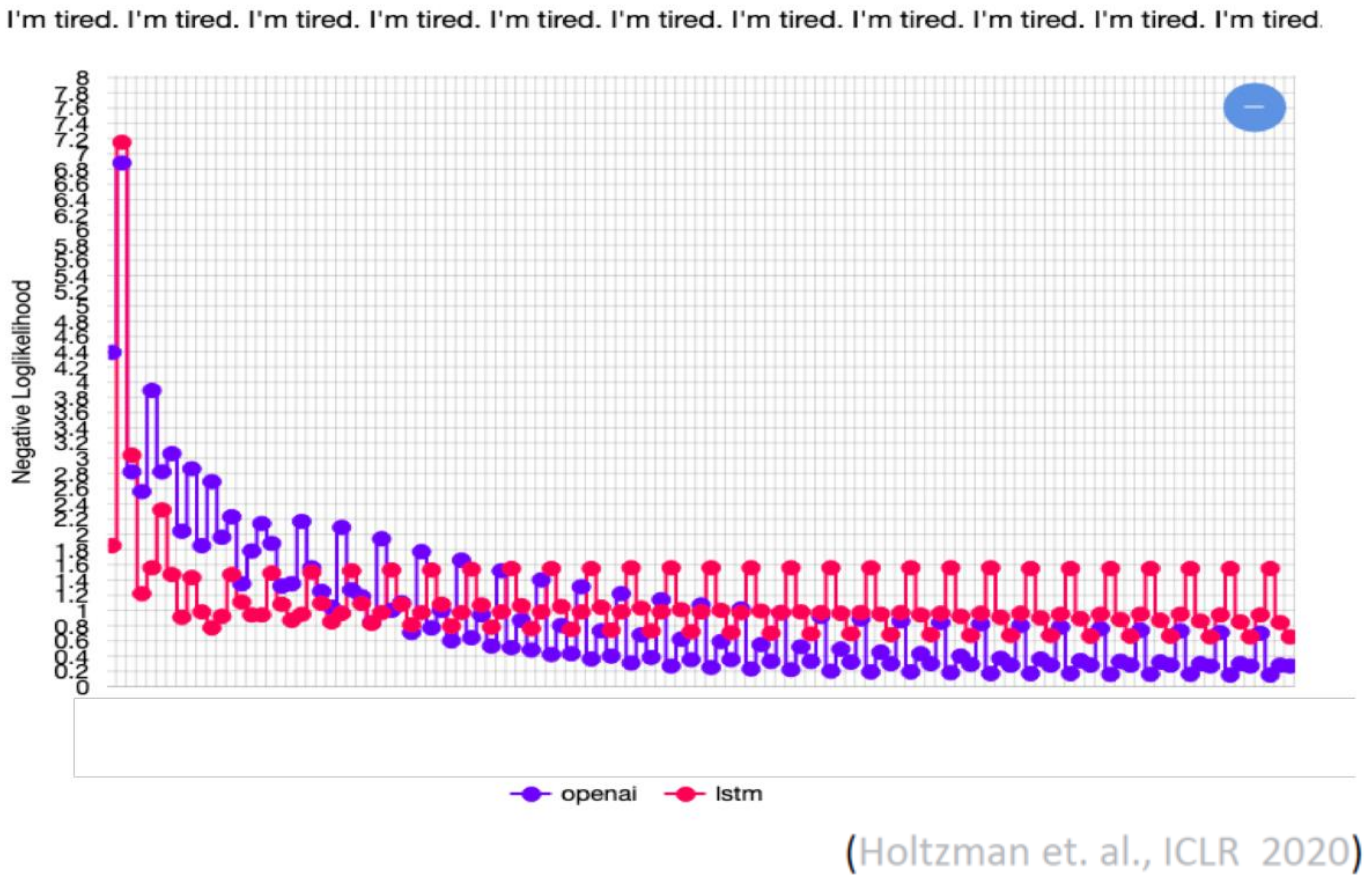
Continuation: The study, published in the Proceedings of the National Academy of Sciences of the United States of America (PNAS), was conducted by researchers from the **Universidad Nacional Autónoma de México (UNAM)** and **the Universidad Nacional Autónoma de México (UNAM/Universidad Nacional Autónoma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

(Holtzman et. al., ICLR 2020)

02 Decoding

Greedy Methods

Greedy methods get repetitive



(Holtzman et. al., ICLR 2020)

- Greedy decoding 방식은 동일한 phrase 를 반복해서 생성하는 문제가 있음
  - Dialogue task 나 chat bot system 같은 open end 문장을 생성할 때 주로 발생됨
- GPT 에선 특정 표현이 반복 생성될 때, 생성 결과에 대해 모델의 confidence 가 높아짐
  - Bottleneck 을 없엔 attention 구조 때문

02 Decoding

Greedy Methods

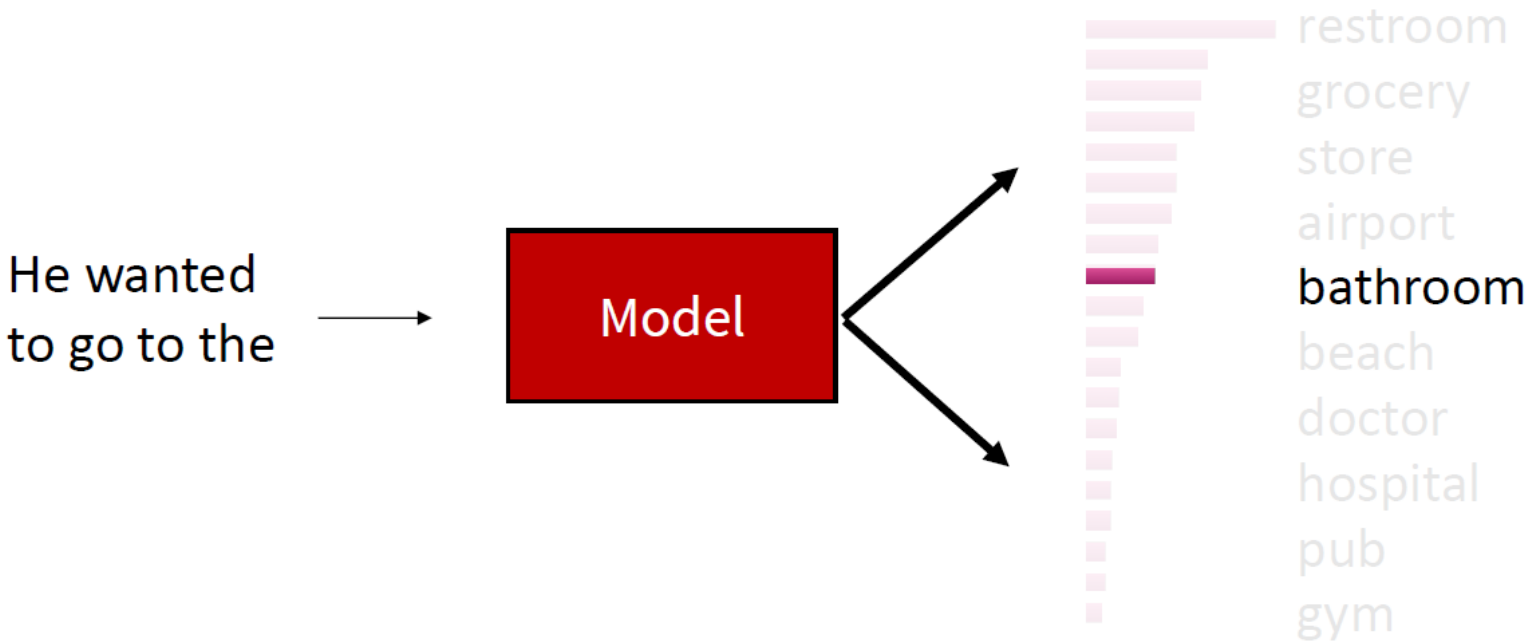
How to reduce

- Decoding 단계에서 n-grams 의 반복을 막음
- 연속되는 문장의 hidden representation similarity 를 낮추는 방식 – 문장 내 반복은 막을 수 없음
- 동일한 단어가 등장하는 것을 막는 attention mechanism : Coverage loss
- 이미 등장한 토큰에 패널티 부여 : Unlikelihood objective
- Decoding 알고리즘 변경
  - Random sampling
  - Top-k sampling
  - Top-p sampling
  - + Scaling randomness : Temperature
  - Re-balancing distributions

02 Decoding

Other Methods

Random sampling

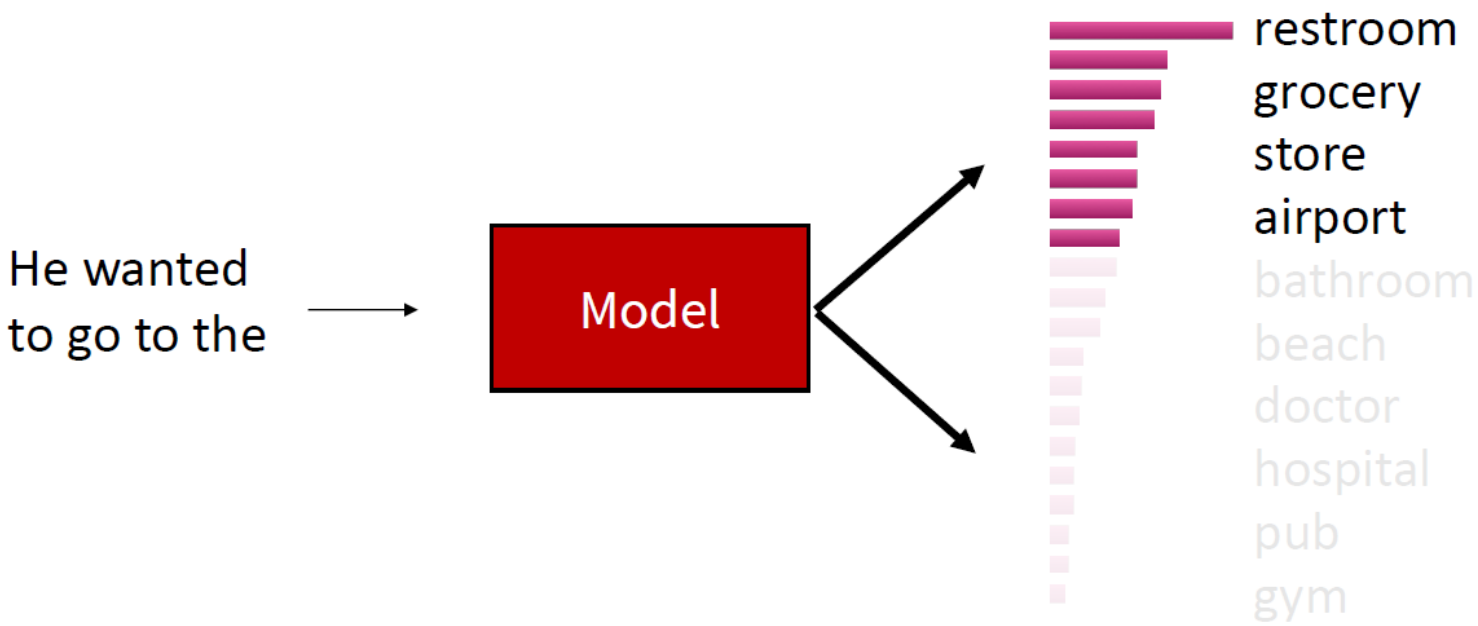


- 토큰 별 distribution 을 sampling 에 사용 → 어떤 단어든(prob≠0) 등장할 수 있음

02 Decoding

Other Methods

Top-k sampling



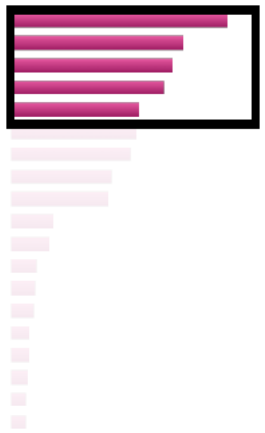
- 토큰 별 distribution 에서 상위 k개에서만 sampling(ex. k=5, 10, 20)
- k ↑ : diverse/risky outputs
- k ↓ : generic/safe outputs

02 Decoding

Other Methods

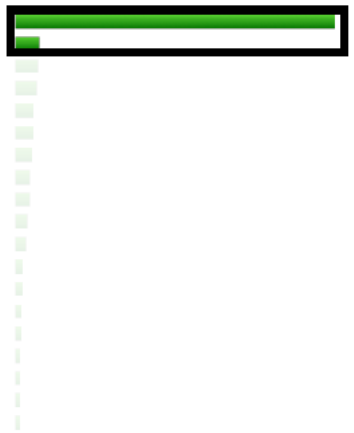
Top-p sampling

$P_t^1(y_t = w \mid \{y\}_{<t})$



$P_t^2(y_t = w \mid \{y\}_{<t})$

$P_t^3(y_t = w \mid \{y\}_{<t})$

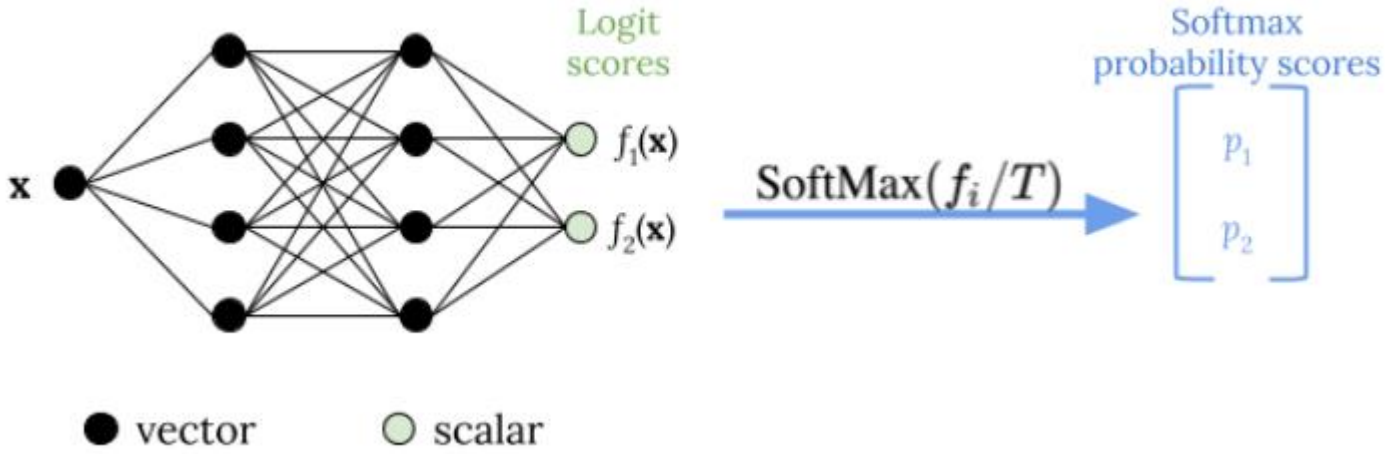


- 누적 확률 값이 p 이상인 토큰들만 샘플링에 사용
- p ↑ : diverse/risky outputs
- p ↓ : generic/safe outputs

02 Decoding

Other Methods

Scaling randomness

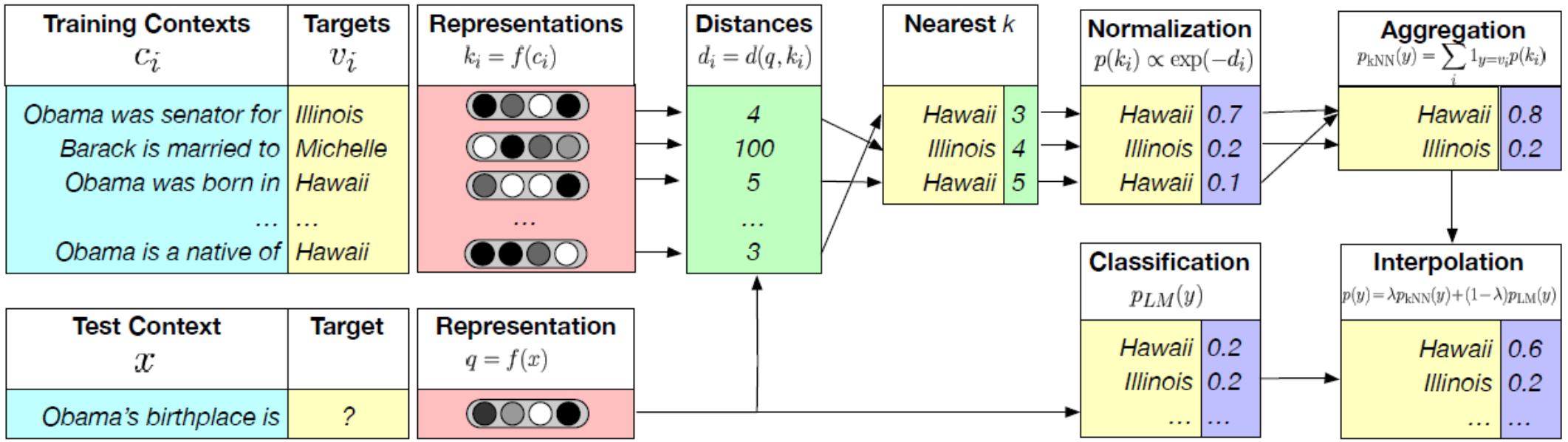


- Logits 값을 상수 T로 나누고 softmax 의 입력으로 사용 (자체가 decoding 알고리즘은 아님)
- T ↑ : diverse/risky outputs, vocab 내 probability 차이가 작아짐
- T ↓ : generic/safe outputs, vocab 내 probability 차이가 커짐

02 Decoding

Other Methods

Re-balancing : kNN-LM

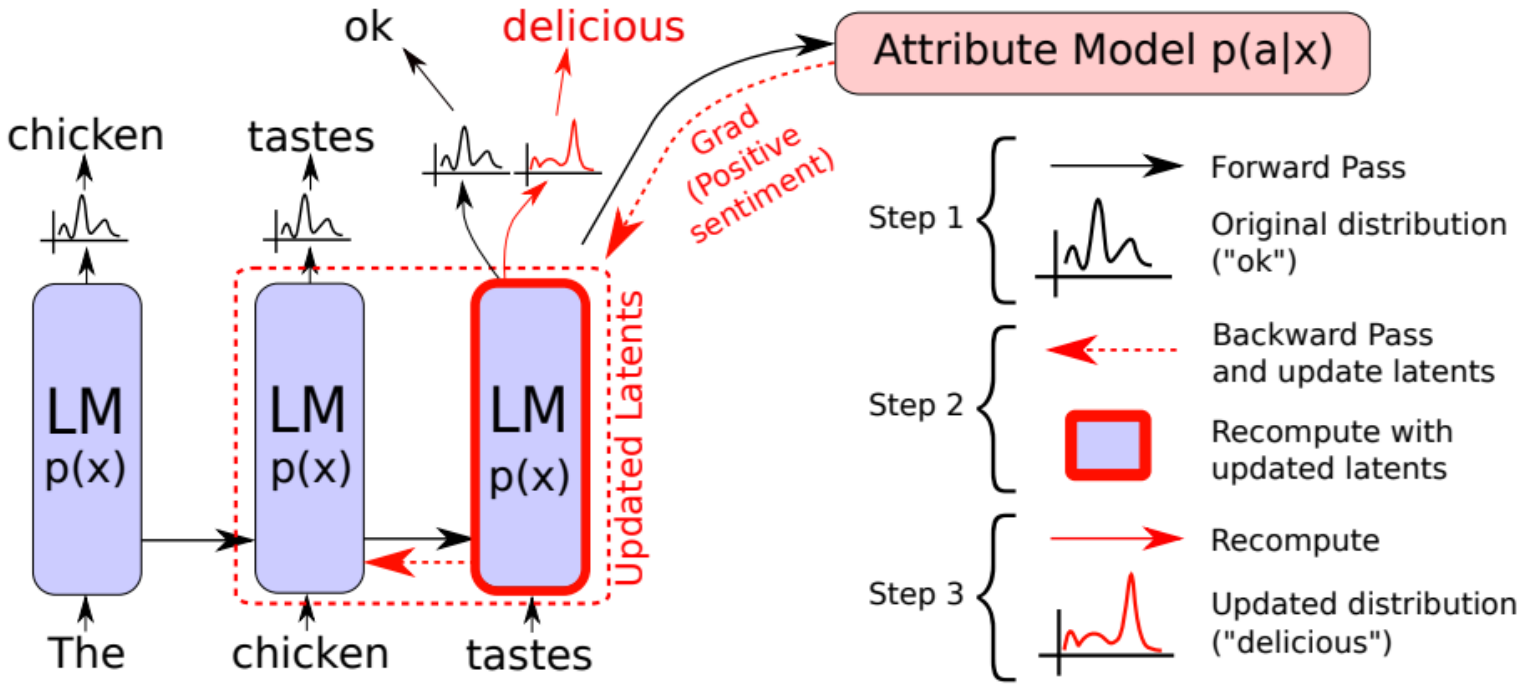


- Inference 시에 평가 문장을 학습된 문장들의 representation 과 비교하여 모델의 토큰 distribution 을 보정해주는 방식
- K 개의 인접한 representation 문장의 target 값을 사용해 모델 평가 결과를 보정

02 Decoding

Other Methods

Re-balancing : PPLM



- 추가적인 모델을 사용해 언어모델의 distribution 조정 (ex. Sentiment, perplexity)
- Attribute model 로부터 gradient 를 전달받아 latent 업데이트 → Model distribution 업데이트

Unlikelihood Training

- 이미 생성된 토큰이 생성될 확률을 낮추는 패널티를 기존 loss function 에 추가함

$$\mathcal{C} = \{y^*\}_{<t}$$

$$\mathcal{L}_{UL}^t = -\sum_{y_{neg} \in \mathcal{C}} \log(1 - P(y_{neg} \mid \{y^*\}_{<t}))$$

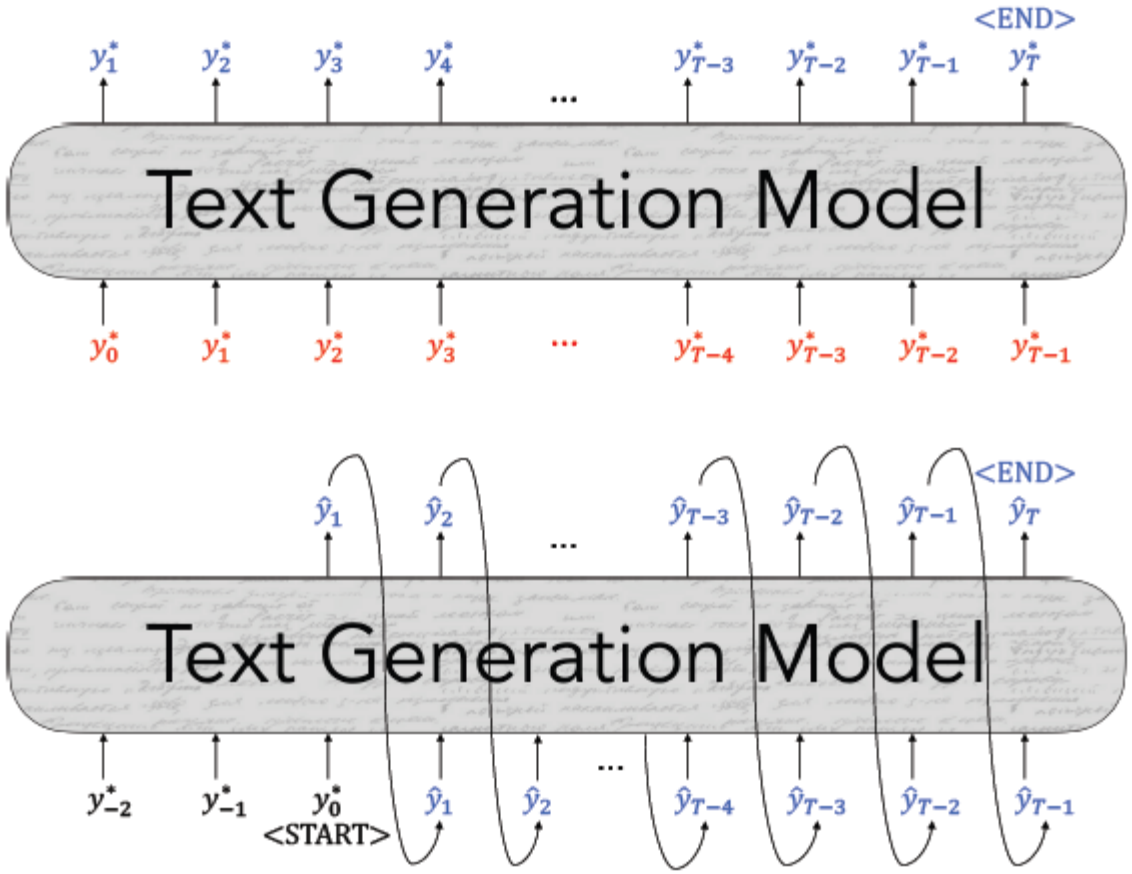
$$\mathcal{L}_{ULE}^t = \mathcal{L}_{MLE}^t + \alpha \mathcal{L}_{UL}^t$$

- 반복된 단어, 구의 생성을 줄일 수 있음
- 생성되는 text 의 다양성을 증가시킴

03 Training

Exposure Bias

Teacher forcing → Bias

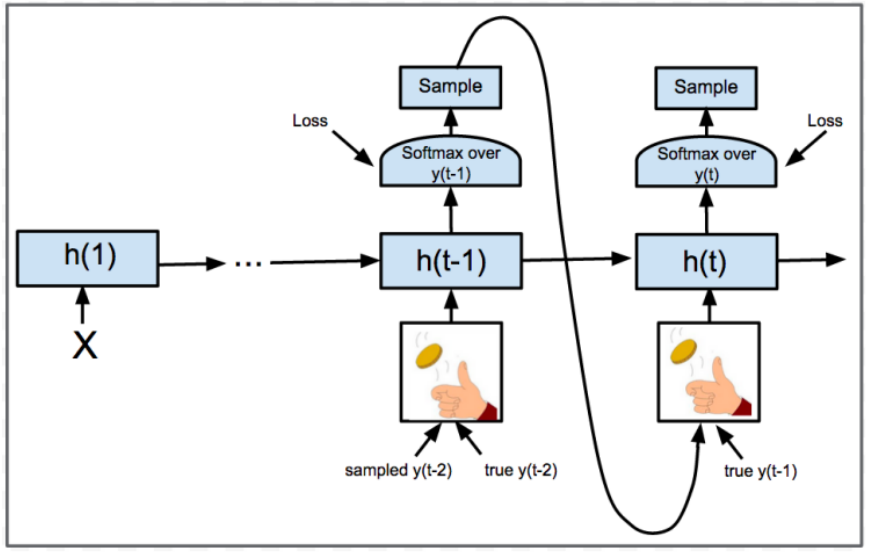


- Teacher forcing 으로 인해 모델이 불필요한 bias 를 학습하게 됨(=overfitting)
- Exposure Bias Solutions
  - Scheduled sampling
  - Dataset Aggregation
  - Sequence re-writing
  - Reinforcement Learning

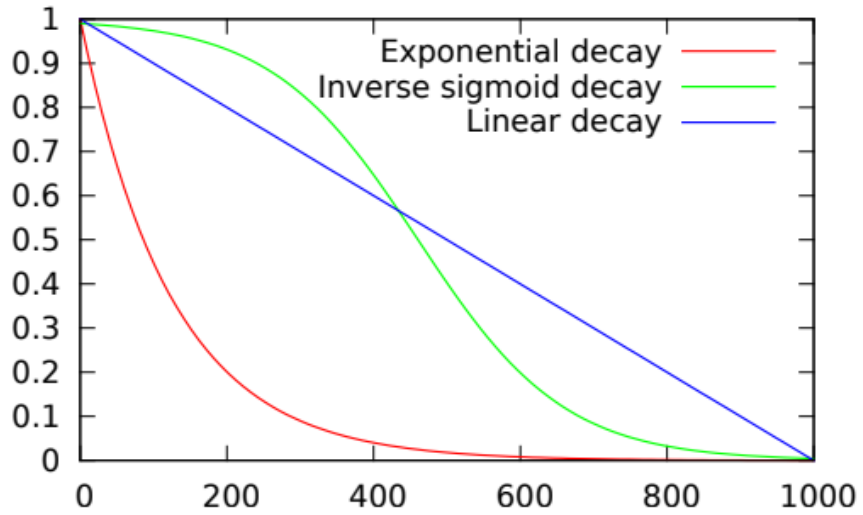
Scheduled sampling

Scheduled Sampling for Sequence Prediction with Recurrent Neural Networks (Bengio et al., 2015)

<Overall framework>



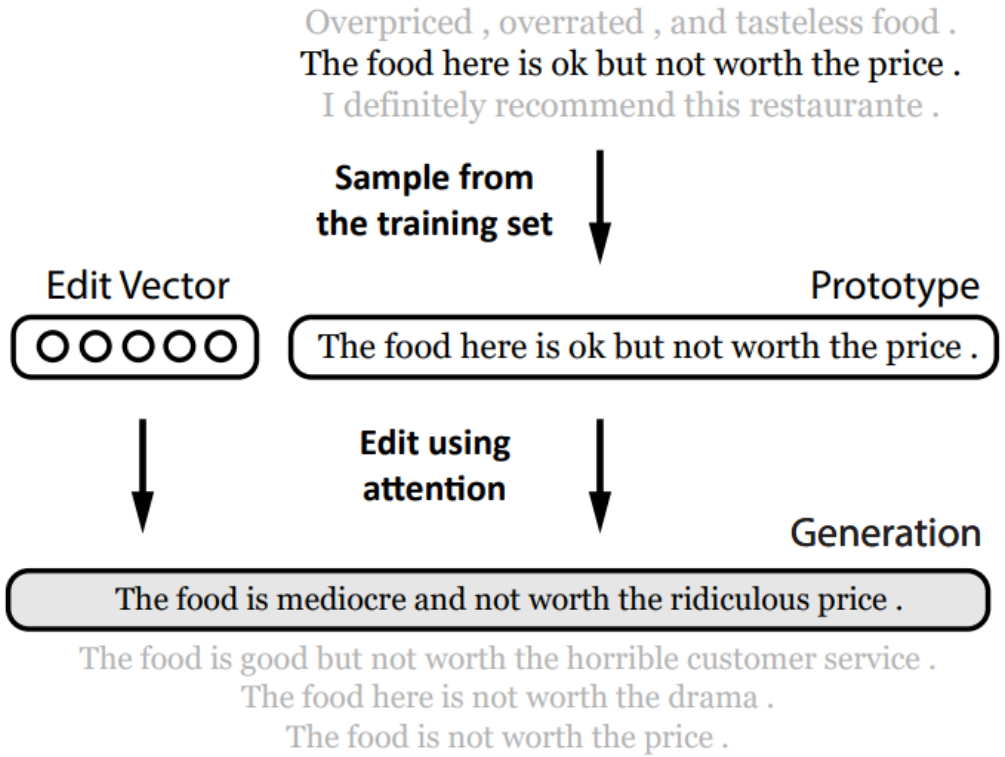
<Decay scheduels>



- 특정확률로 이전 생성된 토큰을 다음 step의 입력으로 사용
- 학습이 진행될 수록 더 적은 gold token 을 사용함

Sequence re-writing

Generating Sentences by Editing Prototypes (Guu, Hashimoto et al., 2018)



- 학습데이터로 구축한 prototype set 을 text 생성에 사용
- 샘플링한 prototype 을 edit vector 를 사용해 변형
  - Adding
  - Removing
  - Modifying tokens

03 Training

Exposure Bias Solutions

Reinforcement Learning

Text 생성모델을 Markov decision process 로 구성

- State : 이전 context 의 representation
- Actions : 현재 step 에서 생성될 수 있는 단어
- Policy : Decoder
- Rewards : score 함수로부터 받게 될 보상 (ex. BLEU, ROUGE, CIDEr, SPIDEr 등이 score 로 사용)

$$\mathcal{L}_{RL} = -\sum_{t=1}^{T} r(\hat{y}_t) \log P(\hat{y}_t | \{y^*\}; \{\hat{y}_t\}_{<t})$$

- Reward Estimation
  - 의도하지 않은 shortcut 을 모델이 학습하지 않도록 reward function 을 잘 정의해야 함

03 Training

Summary

- Teaching forcing 은 여전히 학습 시 많이 사용되는 방식
- Diversity issue
  - 반복된 단어 생성을 막기 위한 연구들이 등장
- Exposure bias issue
  - 모델이 자체적으로 조정하는 방식(scheduled sampling)
  - Bad text 생성을 억제하는 방식(re-writing)

04 Evaluating

Content overlap metrics

N-gram overlap metrics : BLEU

$$BLEU = min(1, \frac{output\ length(\text{예측 문장})}{reference\ length(\text{실제 문장})})(\prod_{i=1}^{4} precision_i)^{\frac{1}{4}}$$

짧은 문장에 대한 penalty

N-gram precision 의 기하평균

- 실제 문장 대비 짧은 문장을 생성할 경우 패널티를 부여
- N-gram precision 의 기하평균 사용
- 일반적으로 많이 사용되는 metric

N-gram overlap metrics : ROUGE

$$\text{ROUGE-N} = \frac{\sum_{S \in \{ReferemceSummaries\}} \sum_{gram_n \in S} Count_{match}(gram_n)}{\sum_{S \in \{ReferenceSummaries\}} \sum_{gram_n \in S} Count(gram_n)}$$

- N-gram recall 사용
- Brevity penalty 가 따로 없음
- BLEU 와는 달리 n-gram 별로 따로 비교함
  (ex. Rouge-1,2,L)

04 Evaluating

Content overlap metrics

N-gram overlap metrics

- Summarization output text 가 길 때, dialogue task 등 open-ended MT에서 적절한 지표가 될 수 없음
- 단어의 문맥적 의미를 반영할 수 없음
- 사람의 평가와 상관성이 낮음

⇒ Semantic overlap metrics, model-based metrics 연구들이 등장함

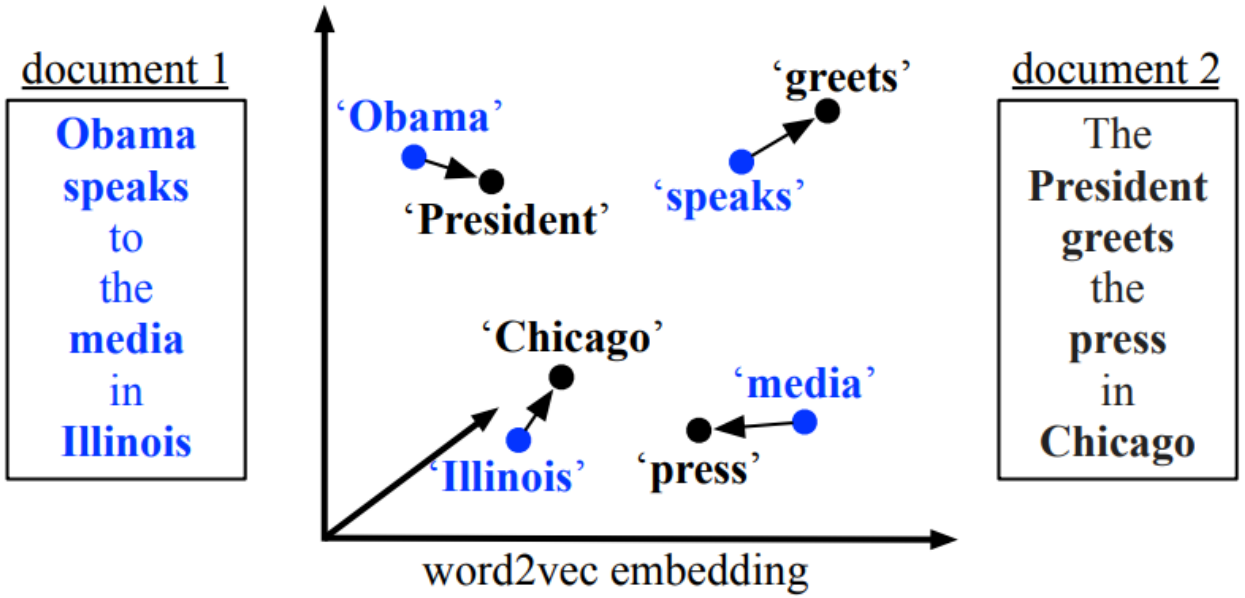
- PYRAMID, SPICE, SPIDER
- Vector Similarity
- Word Mover's Distance
- BERTSCORE
- Sentence Movers Similarity
- BLEURT

04 Evaluating

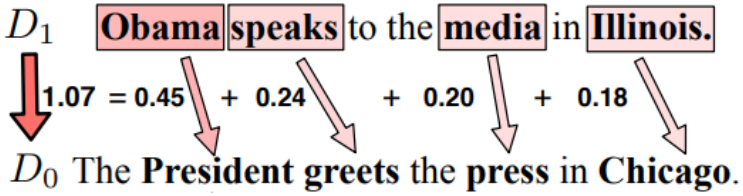
Model-based metrics

Word Mover's Distance

생성 text 와 reference text 의 단어 또는 문장의 semantic similarity 를 계산할 수 있음



- 모든 단어의 word2vec embedding 계산
- Document 1의 모든 단어들의 document 2 까지의 최소 거리 합으로 거리 계산

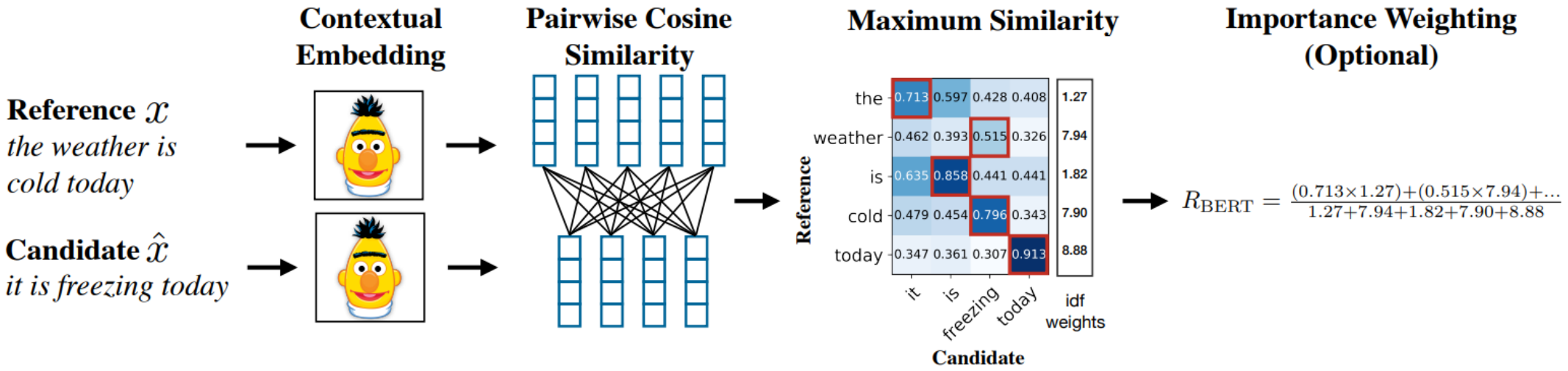


04 Evaluating

Model-based metrics

BERTSCORE

사전 학습 된 BERT 사용



<Recall metric>

- Reference 와 candidate 의 contextual embedding 계산
- 모든 pair 에 대해 cosine similarity 를 계산하고 greedy matching 후 weighted average 를 구함
- Inverse document frequency score 를 사용

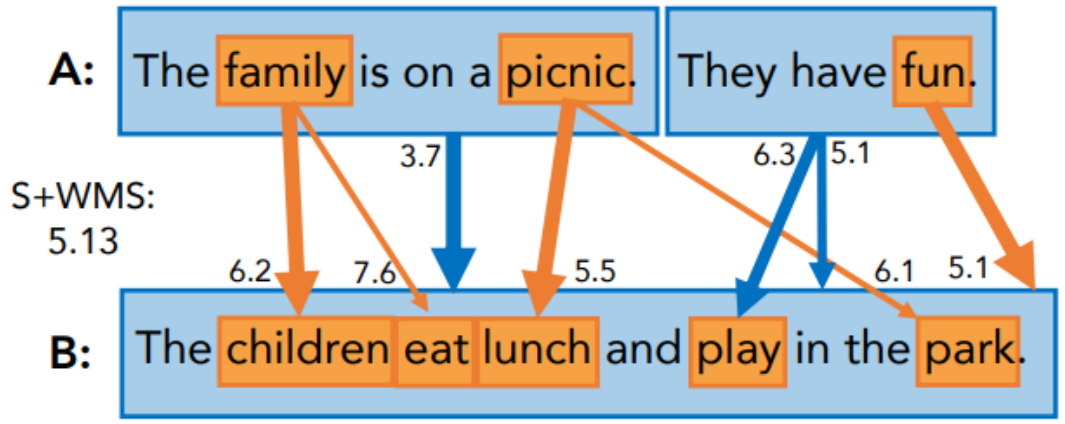
$$\text{idf}(w) = -\log \frac{1}{M} \sum_{i=1}^{M} \mathbb{I}[w \in x^{(i)}]$$

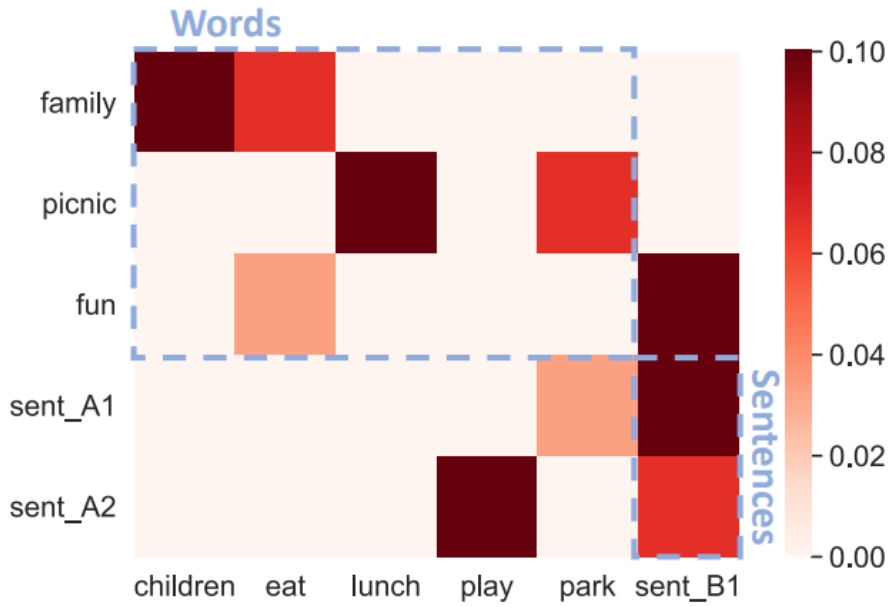
04 Evaluating

Model-based metrics

Sentence Mover's Similarity

Sentence level, word level 에서 모두 similarity 계산





04 Evaluating

Summary

- Content overlap metric 은 가장 단순하면서 직관적이지만 문맥을 전혀 고려하지 못함
- Model-based metric 은 좀 더 사람의 평가와 유사하지만 설명력 부족
- 사람의 평가는 가장 정확하지만 일관성이 떨어짐
- 자연어 생성모델에 대한 평가는 task에 맞게 직접보는 것이 중요하다 !

05 Conclusion

- Ethical considerations
  - 부적절한 bias 가 학습된 언어모델을 pretrained 로 사용할 경우 생성 문장의 부적절한 표현 사용, 고정관념 등으로 사회적 문제를 야기할 수 있음
- NLG task 는 아직 갈 길이 멀다..
- 여러 metric 이 제안되었지만 evaluation 은 여전히 주요 연구과제
  - 사람의 평가와 상관성이 낮음
- Large scale 언어모델 들이 등장하면서 NLG 연구도 새로운 국면을 맞이함
  - 이전 연구들을 활용하여 충분히 개선될 수 있음
- NLG는 NLP 연구주제 중 가장 흥미로운 분야이다!

감사합니다