# Delete, Retrieve, Generate: A Simple Approach to Sentiment and Style Transfer



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## Text Attribute Transfer

Original Sentence: "The gumbo was bland."

Original Attribute: negative sentiment

Target Attribute: positive sentiment

New Sentence: "The gumbo was tasty."



Attribute Transfer



Content Preservation



Grammaticality

# No parallel data

#### **English**

#### French

#### Negative

Positive

The gumbo was bad

Very rude staff

Poorly lit

. . .

The beignets were tasty

I like their jambalaya

Very affordable

• • •



# Delete, Retrieve, Generate



I hated the gumbo Delete



love it Retrieve



I love the gumbo
Generate



## Outline

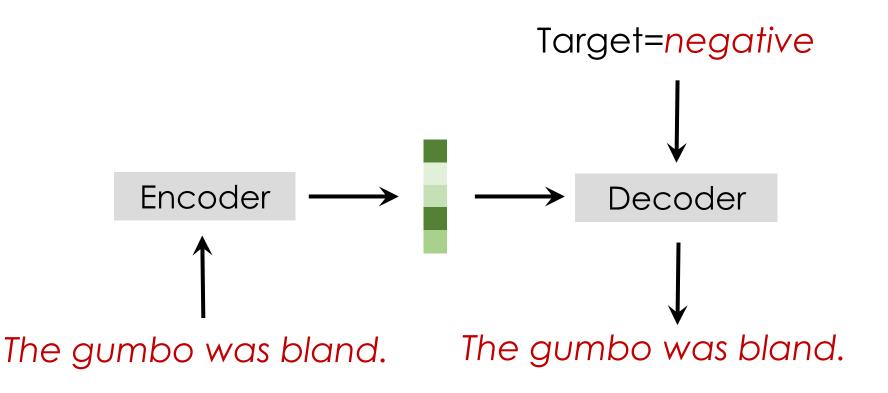
- Prior work with adversarial methods
- Simple baselines
- Simple neural methods



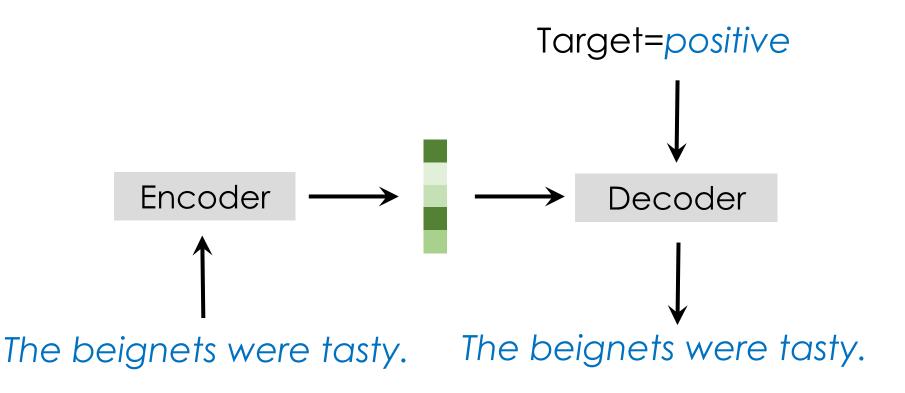
## Outline

- Prior work with adversarial methods
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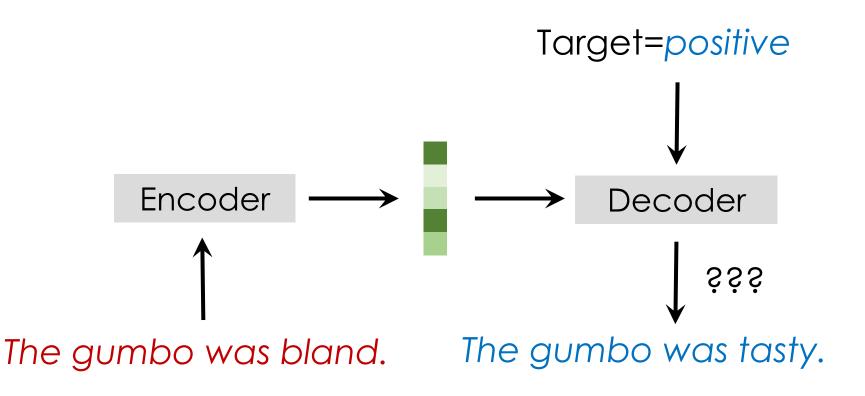




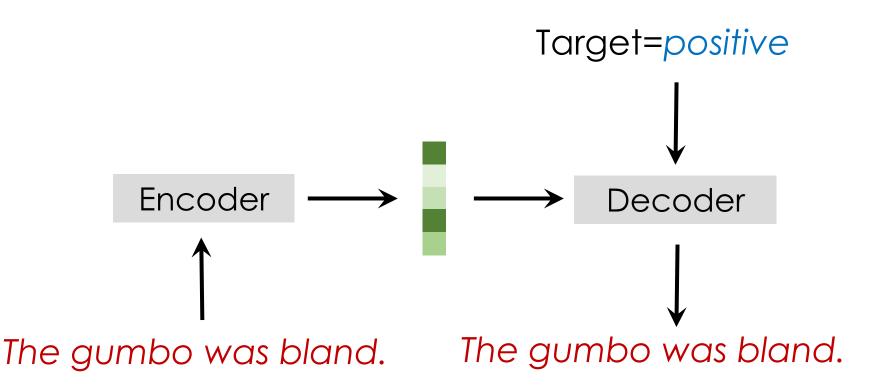








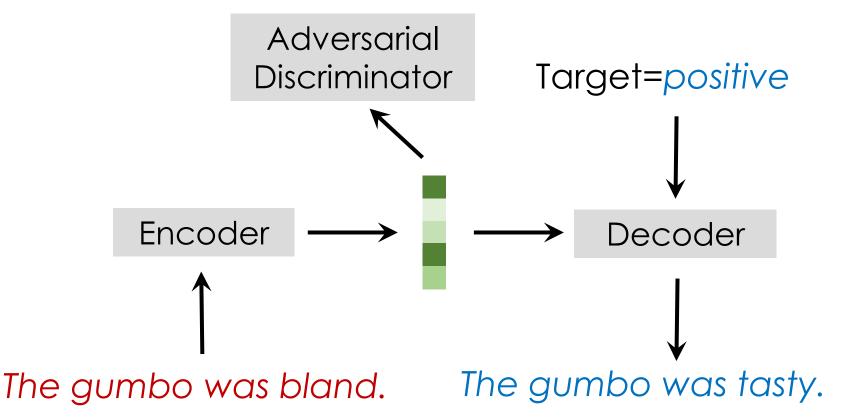




Can copy input and ignore target attribute



# Adversarial content separation



Make discriminator unable to predict attribute



#### **Error Cases**



No Attribute Transfer

Input: "Think twice -- this place is a dump."

Output: "Think twice -- this place is a dump."



#### Error Cases



Content changed

Input: "The queen bed was horrible!"

Output: "The **seafood part** was wonderful!"



#### Error Cases



Poor grammar

Input: "Simply, there are far superior places to go for sushi."

Output: "Simply, there are **far of vegan to go** for sushi."



# A balancing act



Attribute Transfer



Content Preservation



Grammaticality



## Outline

- Prior work with adversarial methods
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- Simple neural methods



# Pick two out of three



Attribute Transfer



Content Preservation



Grammaticality



## Content + Grammar



Content Preservation

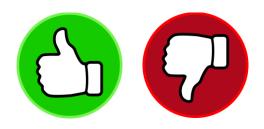


Grammaticality

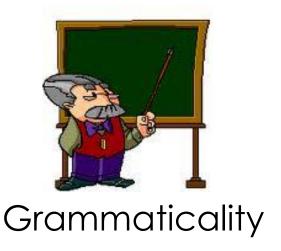
Just return the original sentence...



#### Attribute + Grammar



Attribute Transfer



- Any sentence in the target corpus works!
- Retrieve one that has similar content as input



### Retrieval Baseline

The gumbo was bland

The beignets were tasty
Great prices!
The gumbo was delicious
My wife loved the po'boy





### Retrieval Baseline

The gumbo was bland

The beignets were tasty Great prices!

The gumbo was delicious

My wife loved the po'boy





### Retrieval Baseline

I hated the shrimp

The beignets were tasty
Great prices!
The gumbo was delicious
My wife loved the po'boy





# Content + Attribute



Attribute Transfer



Content Preservation



## Content + Attribute

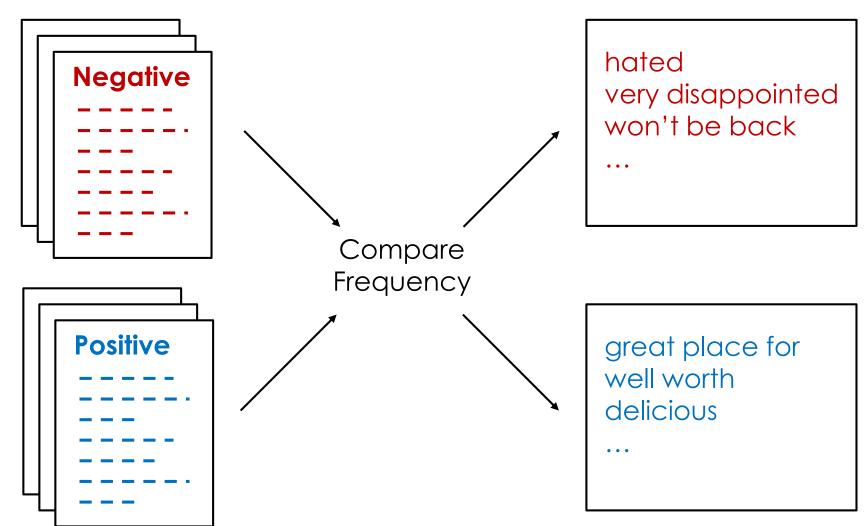
My wife hated the shrimp



- Delete markers of the source attribute
- Replace them with markers of the target attribute



#### Attribute Markers





My wife hated the shrimp





My wife \_\_\_\_\_ the shrimp

loved tasty polite

• • •



My wife \_\_\_\_\_ the shrimp

#### loved

tasty polite

• • •



My wife \_\_\_\_\_ the shrimp

loved tasty polite



My wife \_\_\_\_\_ the shrimp

loved tasty polite



My wife \_\_\_\_\_ the shrimp

**Retrieve** attribute markers from similar contexts

The beignets were tasty
Great prices!
The gumbo was delicious
My wife loved the po'boy





My wife \_\_\_\_\_ the shrimp

**Retrieve** attribute markers from similar contexts

The beignets were tasty
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## Experiments

- Average over 3 datasets
  - Sentiment for Yelp reviews (Shen et al., 2017)
  - Sentiment for Amazon reviews (He and McAuley, 2016; Fu et al., 2018)
  - Factual to Romantic/Humorous style for image captions (Gan et al., 2017)



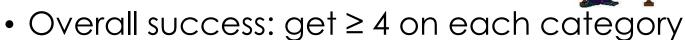
## **Experiments**

- Human Evaluation
  - Likert scale from 1-5 for





- Content preservation
- Grammaticality







Model	Attribute	Content	Grammar	Success
StyleEmbedding (Fu et al., 2018)				12%
MultiDecoder (Fu et al., 2018)				11%
CrossAligned (Shen et al., 2017)				12%



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Retrieval Baseline				23%
Template Baseline				24%



Model	Attribute	Content	Grammar	Success
StyleEmbedding (Fu et al., 2018)	2.6	3.2	3.3	12%
MultiDecoder (Fu et al., 2018)	3.0	2.8	3.1	11%
CrossAligned (Shen et al., 2017)	3.2	2.4	3.3	12%
Retrieval Baseline	3.7	2.7	4.1	23%
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Template Baseline	3.5	3.9	3.2	24%
Human	4.1	4.1	4.4	58%

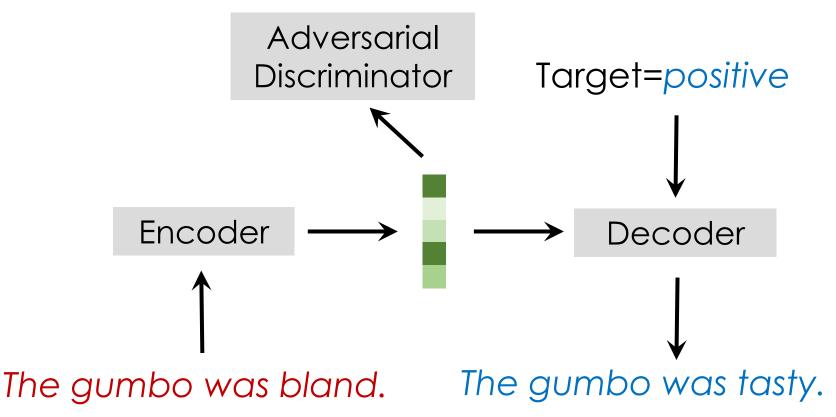


#### Outline

- Prior work with adversarial methods
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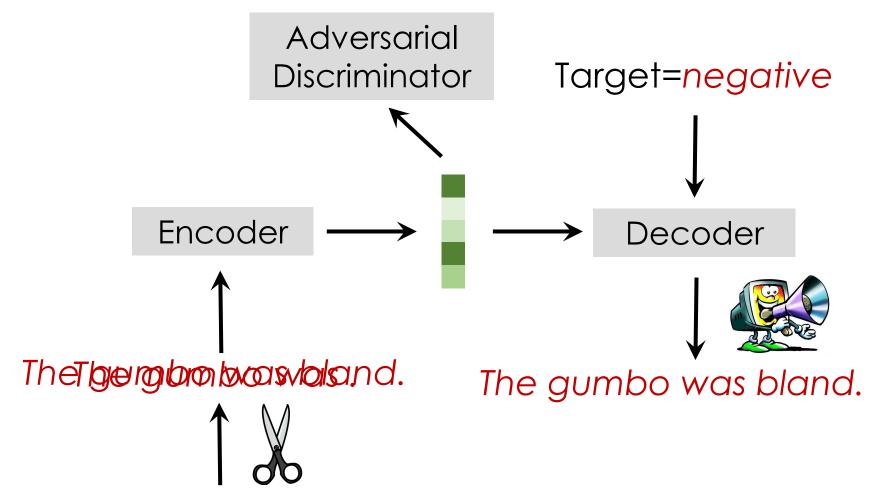
# Content separation revisited



Make discriminator unable to predict attribute

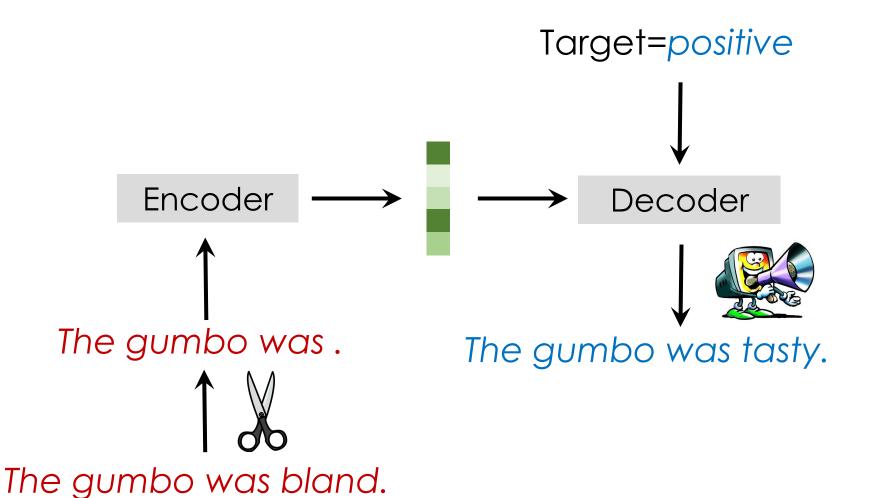


### Delete and Generate





# Delete and Generate





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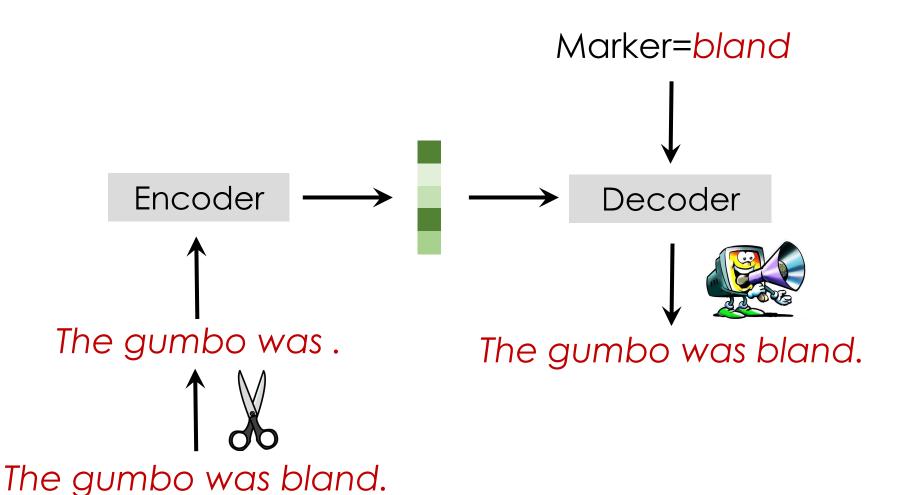


#### Context Cues

Can retrieved attribute markers help the model?

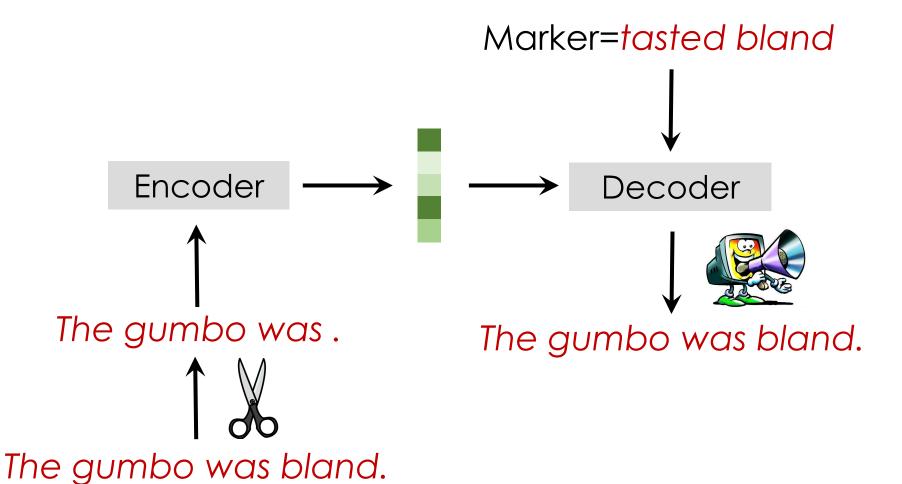


# Delete, Retrieve, Generate



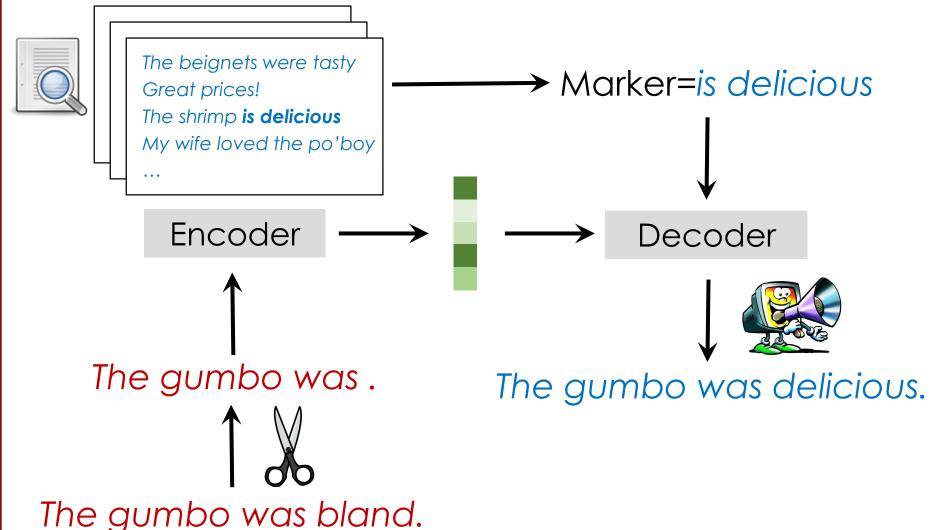


## Delete, Retrieve, Generate





## Delete, Retrieve, Generate





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Delete, Retrieve, Generate	3.7	3.6	3.7	34%
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#### Deleting too much...

Input: "Worst customer service I have ever had."

Output: "Possibly the best chicken I have ever

had."



#### Deleting too little...

Input: "I am actually afraid to open the remaining jars."

Output: "I am actually afraid to open the remaining jars this is great."



### Thank you!



I don't like NLP

Delete



love it

Retrieve



I love NLP

Generate

CodaLab

http://tiny.cc/naacl2018-drg

**GitHub** 

<a href="https://github.com/lijuncen/">https://github.com/lijuncen/</a>
<a href="mailto:Sentiment-and-Style-Transfer">Sentiment-and-Style-Transfer</a>