Trainable Decoding of Sets of Sequences for Neural Sequence Models

Ashwin Kalyan
Peter Anderson
Stefan Lee
Dhruv Batra
Standard Sequence Prediction Pipeline

1. Train RNNs to maximize Log Likelihood
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2. Perform Beam Search to decode top K
Trainable Decoding of Sets of Sequences for Neural Sequence Models

Standard Sequence Prediction Pipeline

1. Train RNNs to maximize Log Likelihood

2. Perform Beam Search to decode top K

3. Return the best sequence in the top K

\[ y_t \rightarrow h_t \rightarrow RNN \\]

\[ h_{t-1} \rightarrow h_t \rightarrow RNN \\]

\[ o_t \rightarrow y_t \rightarrow y_{t+1} \]

\[ B = 2 \]

\[ This \]

\[ a \]

\[ the \]

\[ shows \]

\[ is \]

\[ picture \]

> A kitchen with a stove.
> A kitchen with a stove and a sink.
> A kitchen with a stove and a microwave.
> A kitchen with a stove and a refrigerator.
But... many real world tasks are multi-modal!

- A group of people riding horses.
- Kids riding horses with adults help.
- A girl poses on her horse in equestrian dress by a small crowd.
- Some people stand near some horses in a field.
- People are standing around children riding horses in a grassy area.
- A small girl is riding a large light brown horse.
- A young girl in riding gear mounts a pony in front of a group.
- A group of people with a jockey and her horse
- Several people playing with ponies in a park.

How to model more than one correct output?
Retool the Standard Sequence Prediction Pipeline

1. Train RNNs to maximize Log Likelihood

2. Perform Beam Search to decode top $K$

3. Return the best sequence in the top $K$
Retool the Standard Sequence Prediction Pipeline

1. Train RNNs to maximize Log Likelihood

\[
\begin{align*}
O_t & \quad h_t \\
h_{t-1} & \quad y_t \\
y_t & \quad y_{t+1}
\end{align*}
\]

2. Perform Beam Search to decode top K

\[
B = 2
\]

3. Return the best sequence in the top K

> A kitchen with a stove.
> A kitchen with a stove and a microwave.
> A kitchen with a stove and a sink.
> A kitchen with a stove and a refrigerator.
Beam Search outputs are nearly identical!

- A group of people riding horses on a field.
- A group of people riding horses in a field.
- A group of people riding horses down a dirt road.
- A group of people riding horses through a field.
- A group of people riding on the back of horses.
- A group of people riding on the back of a horse.
- A group of people riding on a horse.
- A couple of people riding on the back of horses.
- A couple of people riding on the back of a horse.
- A couple of people riding horses on a field.

Doesn’t model intra-set interactions!
Beam Search outputs are nearly identical!

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Doesn’t model intra-set interactions!

Fails to COVER the variation in the output space!
Learning to Decode Sets of Sequences

*Select top-$B$ words at each time step*

$$B = 2$$
Learning to Decode Sets of Sequences

Select top-$B$ words at each time step

$B = 2$

This

picture

is

the

shows

is

a
Learning to Decode Sets of Sequences

Select top-$B$ words at each time step

$B = 2$

This is a picture shows
Learning to Decode Sets of Sequences

Select top-B words at each time step

\[ B = 2 \]

This

is

a

picture

shows

Till end token is generated or max time
Beam Search as Subset Selection

\[ |\mathcal{V}| \times B \]
Beam Search as Subset Selection

$$|\mathcal{V}| \times B$$
Beam Search as Subset Selection

$|\mathcal{V}| \times B$

Incoming beams

All possible expansions

Outgoing beams

EXPAND

SUBMODULAR MAXIMIZATION
Submodular Maximization for Subset Selection

$|V| \times B$

- Naturally models coverage, promoting diversity
Submodular Maximization for Subset Selection

\[ |V| \times B \]

- Naturally models coverage, promoting diversity
- NP Hard!
Submodular Maximization for Subset Selection

\[ |\mathcal{V}| \times B \]

- Naturally models coverage, promoting diversity
- NP Hard!
- Greedy algorithms with approximation guarantees exist!
Learning Submodular Functions

\[ \forall e \in S, \phi(e) \geq 0 \]

Set feature

\[ \sum_{i} w_i \]

\[ w_i \geq 0 \]

MLP

\[ W \geq 0 \]

\[ \log(1 + \cdot) \]

\[ f(S) \]

[Bilmes et al., 2017]
\[ \nabla \text{BS (diff-BS)} \]

FOR $t = 1$ to $T$:
1. Construct set of all possible extensions
   \[ V_{t-1} \times |V| \]
FOR $k = 1$ to $K$:
2. Compute marginal gain of each extension
3. Sample an extension proportional to marginal gain
RETURN Set of $K$ Sequences of length $T$
FOR $t = 1$ to $T$:

1. Construct set of all possible extensions
   $$\mathcal{Y}_{t-1} \times |\mathcal{V}|$$

FOR $k = 1$ to $K$:

2. Compute marginal gain of each extension
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RETURN Set of $K$ Sequences of length $T$
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$$\nabla \text{BS (diff-BS)}$$

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1. \text{ Construct set of all possible extensions } & \mathcal{Y}_{t-1} \times |\mathcal{V}| \\
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2. \text{ Compute marginal gain of each extension } & \\
3. \text{ Sample an extension proportional to marginal gain } & \\
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\end{align*}
“Set of Sequences” Level Training

\[ \pi^* = \arg \max_{\pi \in \Pi} \mathbb{E}_{(Y_1, \ldots, Y_T) \sim \pi(\cdot | x)} SET - METRIC(Y \mid x) \]
“Set of Sequences” Level Training

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- Set-metric?
  - Oracle, average accuracy
"Set of Sequences" Level Training

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  - Oracle, average accuracy
  - Facility Location Accuracy [NEW]
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- Training?
  - Teacher Forcing if multiple annotations are available.
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  - Imitation Learning if expert is available
“Set of Sequences” Level Training

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\pi^* = \arg \max_{\pi \in \Pi} \mathbb{E}_{(Y_1, \ldots, Y_T) \sim \pi(\cdot|\mathbf{x})} \text{SET-METRIC}(\mathbf{Y}|\mathbf{x})
\]

• Set-metric?
  • Oracle, average accuracy
  • Facility Location Accuracy [NEW]

• Training?
  • Teacher Forcing if multiple annotations are available
  • Imitation Learning if expert is available
  • REINFORCE to directly optimize for the set-metric
In Summary

• Novel perspective. Beam Search as Subset Selection
• Models intra-set dependencies
• Can be used with arbitrary set constraints
• No train-test or loss-evaluation mismatch
• Outperforms Beam Search and other baselines on captioning

Doesn’t scale very well with beam size (some tricks in the paper)
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Poster: Pacific Ballroom #48
June 13th 6:30 pm

Code: https://github.com/ashwinkalyan/diff-bs