Natural Language Processing with Deep Learning

CS224N/Ling284

Lecture 15:
Natural Language Generation

Christopher Manning

Announcements

Thank you for all your hard work!

- We know Assignment 5 was tough and a real challenge to do
- … and project proposal expectations were difficult to understand for some
- We *really appreciate* the effort you're putting into this class!
- Do get underway on your final projects – and good luck with them!

Overview

Today we'll be learning about what's happening in the world of neural approaches to **Natural Language Generation (NLG)**

Plan for today:

- Recap what we already know about NLG
- More on decoding algorithms
- NLG tasks and neural approaches to them
- NLG evaluation: a tricky situation
- Concluding thoughts on NLG research, current trends, and the future

Section 1:
Recap: LMs and decoding algorithms

Natural Language Generation (NLG)

- Natural Language Generation refers to any setting in which we *generate* (i.e. write) new text.

- NLG is a subcomponent of:
  - Machine Translation
  - (Abstractive) Summarization
  - Dialogue (chit-chat and task-based)
  - Creative writing: storytelling, poetry-generation
  - Freeform Question Answering (i.e. answer is generated, not extracted from text or knowledge base)
  - Image captioning
  - …

Recap

- **Language Modeling**: the task of predicting the next word, given the words so far

$$P(y_t | y_{1,\ldots,}y_{t-1})$$

- A system that produces this probability distribution is called a **Language Model**

- If that system is an RNN, it's called an **RNN-LM**

Recap

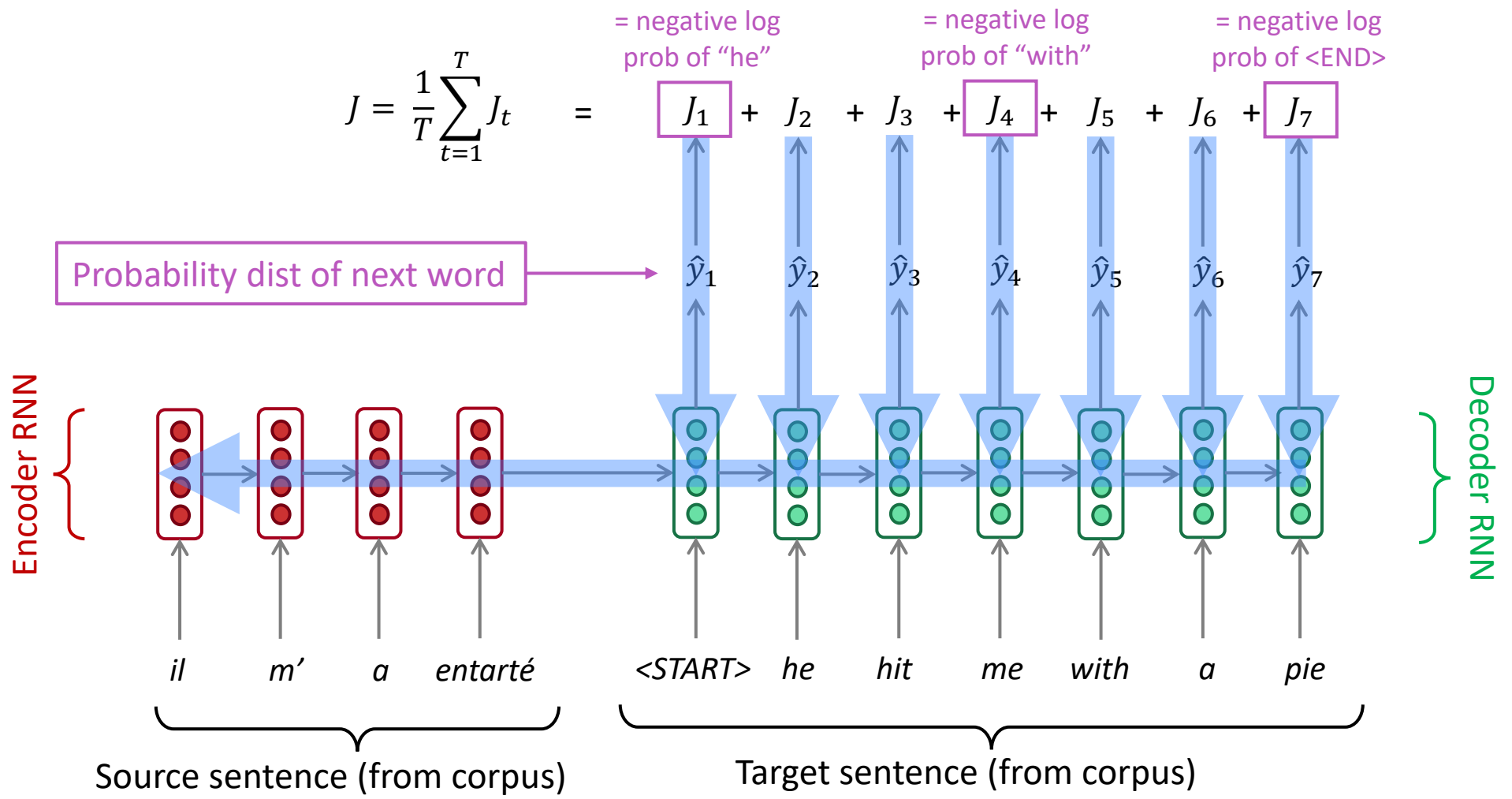
- **Conditional** Language Modeling: the task of predicting the next word, given the words so far, and also some other input *x*

$$P(y_t | y_{1,\ldots,} y_{t-1}, x)$$

- Examples of conditional language modeling tasks:
  - Machine Translation (*x*=source sentence, *y*=target sentence)
  - Summarization (*x*=input text, *y*=summarized text)
  - Dialogue (*x*=dialogue history, *y*=next utterance)
  - …

Recap: training a (conditional) RNN-LM

This example: Neural Machine Translation



During training, we feed the gold (aka reference) target sentence into the decoder, regardless of what the decoder predicts. This training method is called ***Teacher Forcing***.

Recap: decoding algorithms

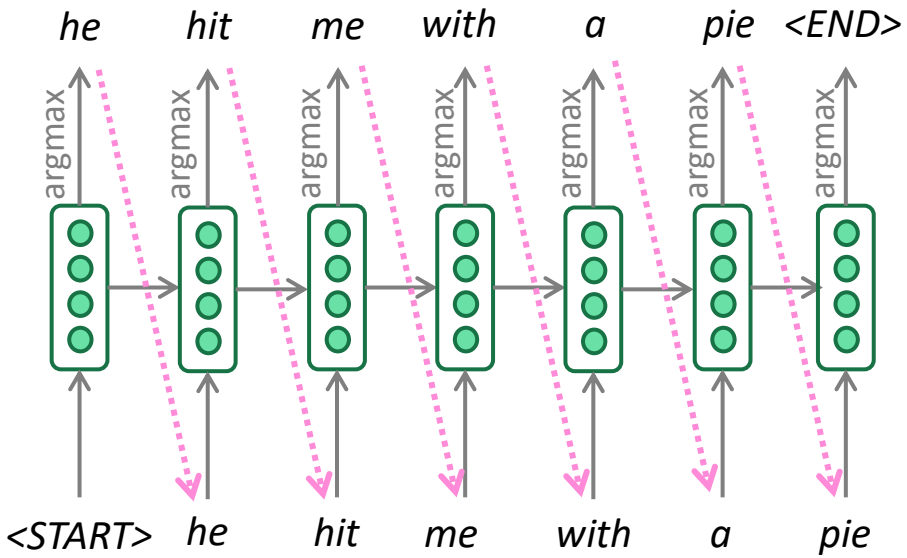
- Question: Once you've trained your (conditional) language model, how do you use it to generate text?

- Answer: A *decoding algorithm* is an algorithm you use to generate text from your language model

- We've learned about two decoding algorithms:
  - Greedy decoding
  - Beam search

Recap: greedy decoding

- A simple algorithm
- On each step, take the most probable word (i.e. argmax)
- Use that as the next word, and feed it as input on the next step
- Keep going until you produce <END> (**or reach some max length**)



- Due to lack of backtracking, output can be poor
  (e.g. ungrammatical, unnatural, nonsensical)

Recap: beam search decoding

- A search algorithm which aims to find a high-probability sequence (not necessarily the optimal sequence, though) by tracking multiple possible sequences at once.

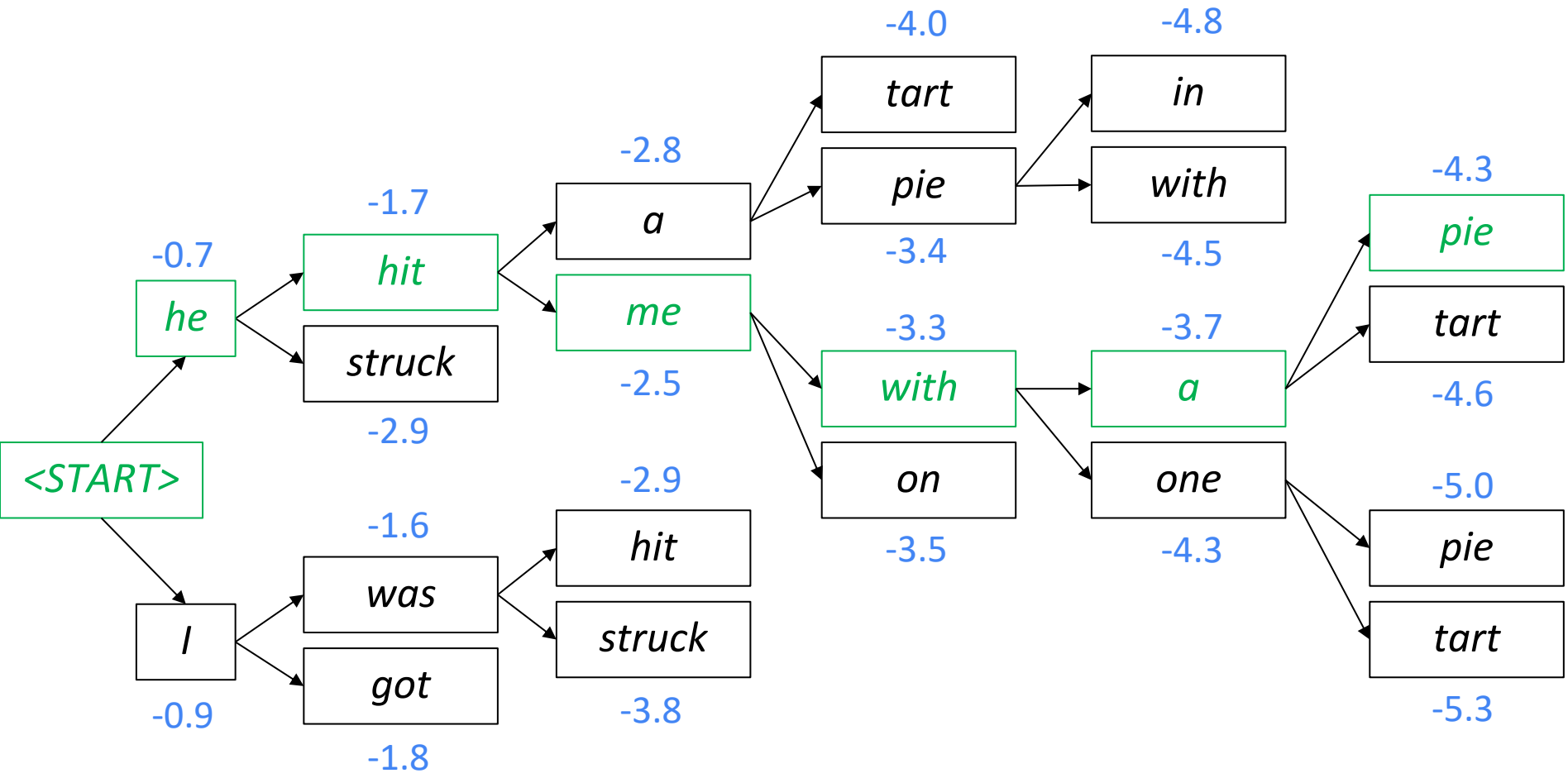
- Core idea: On each step of decoder, keep track of the *k* most probable partial sequences (which we call *hypotheses*)
  - *k* is the beam size

- Expand hypotheses and then trim to keep only the best *k*

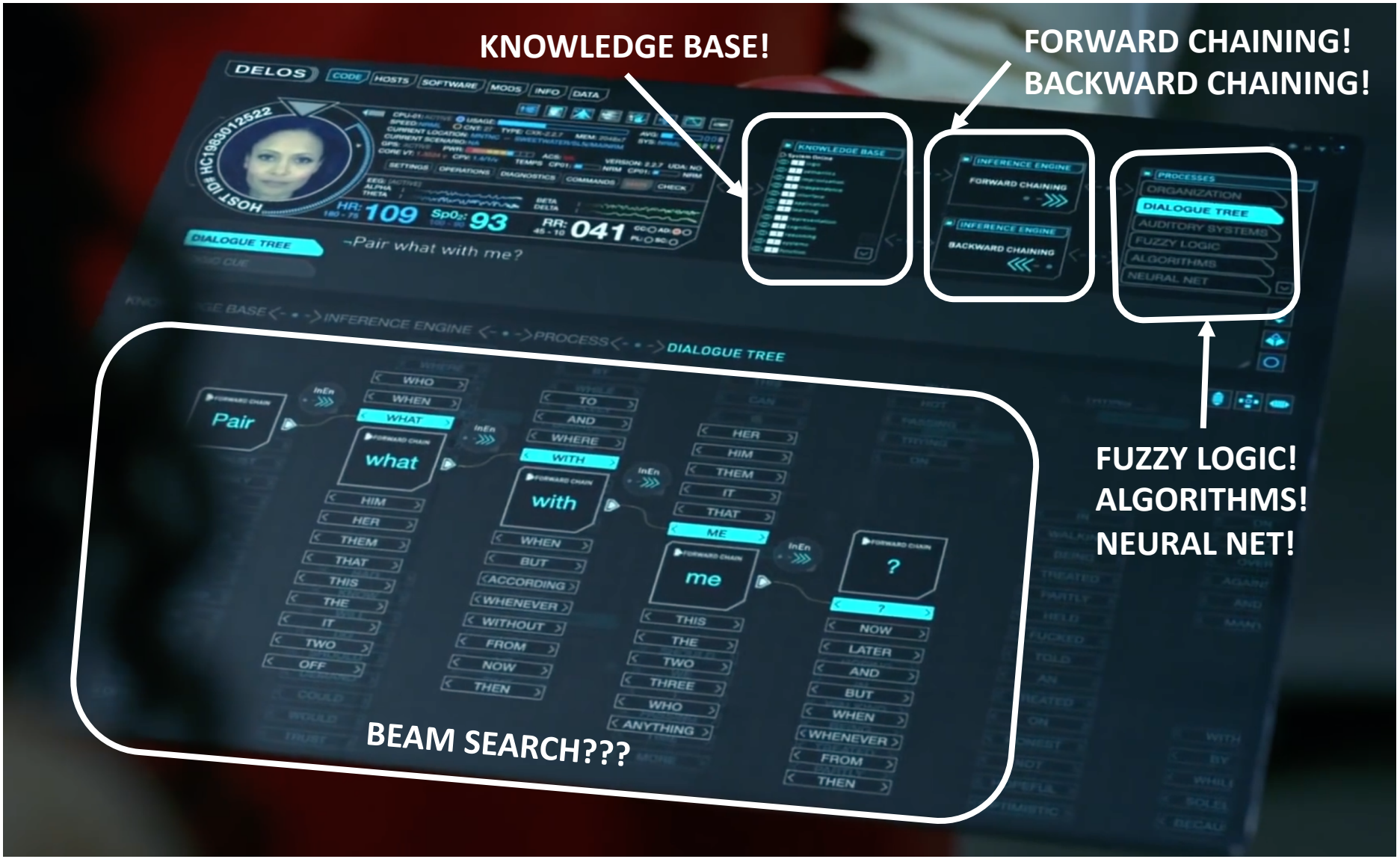
- After you reach some stopping criterion, choose the sequence with the highest probability (factoring in some adjustment for length)

Recap: beam search decoding

Beam size = *k* = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$



Aside: Do the hosts in *Westworld* use beam search?



Source: https://www.youtube.com/watch?v=ZnxJRYit44k

What's the effect of changing beam size *k*?

- Small *k* has similar problems to greedy decoding (*k*=1)
  - Ungrammatical, unnatural, nonsensical, incorrect

- Larger *k* means you consider more hypotheses
  - Increasing *k* reduces some of the problems above
  - Larger *k* is more computationally expensive
  - But increasing *k* can introduce other problems:
    - For NMT, increasing *k* too much decreases BLEU score (Tu et al, Koehn et al). This is primarily because large-k beam search produces too-short translations (even with score normalization!)
      - It can even produce empty translations (Stahlberg & Byrne 2019)
    - In open-ended tasks like chit-chat dialogue, large *k* can make output more generic (see next slide)

Neural Machine Translation with Reconstruction, Tu et al, 2017 https://arxiv.org/pdf/1611.01874.pdf
Six Challenges for Neural Machine Translation, Koehn et al, 2017 https://arxiv.org/pdf/1706.03872.pdf

Effect of beam size in chitchat dialogue

I mostly eat a fresh and raw diet, so I save on groceries

Human chit-chat partner

Beam size	Model response
1	*I love to eat healthy and eat healthy*
2	*That is a good thing to have*
3	*I am a nurse so I do not eat raw food*
4	*I am a nurse so I am a nurse*
5	*Do you have any hobbies?*
6	*What do you do for a living?*
7	*What do you do for a living?*
8	*What do you do for a living?*

Low beam size:
More on-topic but nonsensical; bad English

High beam size:
Converges to safe, "correct" response, but it's generic and less relevant

Sampling-based decoding

Both of these are **more efficient** than beam search – no multiple hypotheses

ie more quick to compute no need to search

- Pure sampling
  - On each step *t*, randomly sample from the probability distribution P_t to obtain your next word.
  - Like greedy decoding, but sample instead of argmax.

- Top-n sampling*
  - On each step *t*, randomly sample from P_t, restricted to just the top-n most probable words
  - Like pure sampling, but truncate the probability distribution
  - *n=1* is greedy search, *n=V* is pure sampling
  - Increase *n* to get more diverse/risky output
  - Decrease *n* to get more generic/safe output

*Usually called top-*k* sampling, but here we're avoiding confusion with beam size *k*

Sampling-based decoding

- Top-p sampling
  - On each step *t*, randomly sample from P_t, restricted to just the top-p proportion of the most probable words
  - Again, like pure sampling, but truncating the probability distribution
  - This way you get a bigger sample when probability mass is spread
  - Seems like it may be even better

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, Yejin Choi. The Curious Case of Neural Text Degeneration. *ICLR 2020.*

Softmax temperature

- Recall: On timestep t, the LM computes a prob dist P_t by applying the softmax function to a vector of scores $s \in \mathbb{R}^{|V|}$

$$P_t(w) = \frac{\exp(s_w)}{\sum_{w' \in V} \exp(s_{w'})}$$

- You can apply a *temperature hyperparameter* τ to the softmax:

$$P_t(w) = \frac{\exp(s_w/\tau)}{\sum_{w' \in V} \exp(s_{w'}/\tau)}$$

- Raise the temperature τ: P_t becomes more uniform
  - Thus more diverse output (probability is spread around vocab)
- Lower the temperature τ: P_t becomes more spiky
  - Thus less diverse output (probability is concentrated on top words)

Note: softmax temperature is not a decoding algorithm!
It's a technique you can apply at test time, in conjunction with a decoding algorithm (such as beam search or sampling)

Decoding algorithms: in summary

- **Greedy decoding** is a simple method; gives low quality output
- **Beam search** (especially with high beam size) searches for high-probability output
  - Delivers better quality than greedy, but if beam size is too high, can return high-probability but unsuitable output (e.g. generic, short)
- **Sampling methods** are a way to get more diversity and randomness
  - Good for open-ended / creative generation (poetry, stories)
  - Top-n/p sampling allows you to control diversity
- **Softmax temperature** is another way to control diversity
  - It’s not a decoding algorithm! It's a technique that can be applied alongside any decoding algorithm.

Section 2:
NLG tasks and neural approaches to them

Summarization: task definition

Task: given input text *x*, write a summary *y* which is shorter and contains the main information of *x*.

Summarization can be single-document or multi-document.

- Single-document means we write a summary *y* of a single document *x*.

- Multi-document means we write a summary *y* of *multiple* documents $x_1,\ldots,x_n$

  Typically $x_1,\ldots,x_n$ have overlapping content: e.g. news articles about the same event

Summarization: task definition

Within single-document summarization, there are datasets with source documents of different lengths and styles:

- Gigaword: first one or two sentences of a news article → headline (aka *sentence compression*)
- LCSTS (Chinese microblogging): paragraph → sentence summary
- NYT, CNN/DailyMail: news article → (multi)sentence summary
- Wikihow: full how-to article → summary sentences
- XSum: (Narayan et al., 2018), Newsroom: (Grusky et al., 2018): article → 1 sentence summary (New datasets!)

Sentence simplification is a different but related task:
rewrite the source text in a simpler (sometimes shorter) way

- Simple Wikipedia: standard Wikipedia sentence → simple version
- Newsela: news article → version written for children

List of summarization datasets, papers, and codebases: https://github.com/mathsyouth/awesome-text-summarization

Summarization: two main strategies

Extractive summarization

Select parts (typically sentences) of the original text to form a summary.

- Easier
- Restrictive (no paraphrasing)

Abstractive summarization

Generate new text using natural language generation techniques.

- More difficult
- More flexible (more human)

Pre-neural summarization

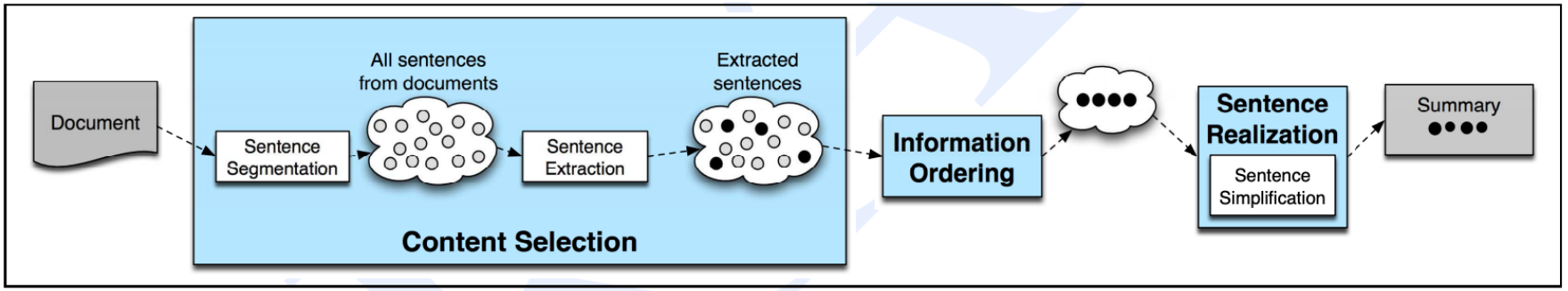


Figure 23.14 The basic architecture of a generic single document summarizer.

- Pre-neural summarization systems were mostly extractive

- Like pre-neural MT, they typically had a pipeline:
  - **Content selection**: choose some sentences to include
  - **Information ordering**: choose an ordering of those sentences
  - **Sentence realization**: edit the sequence of sentences (e.g. simplify, remove parts, fix continuity issues)

Diagram credit: *Speech and Language Processing*, Jurafsky and Martin

Pre-neural summarization

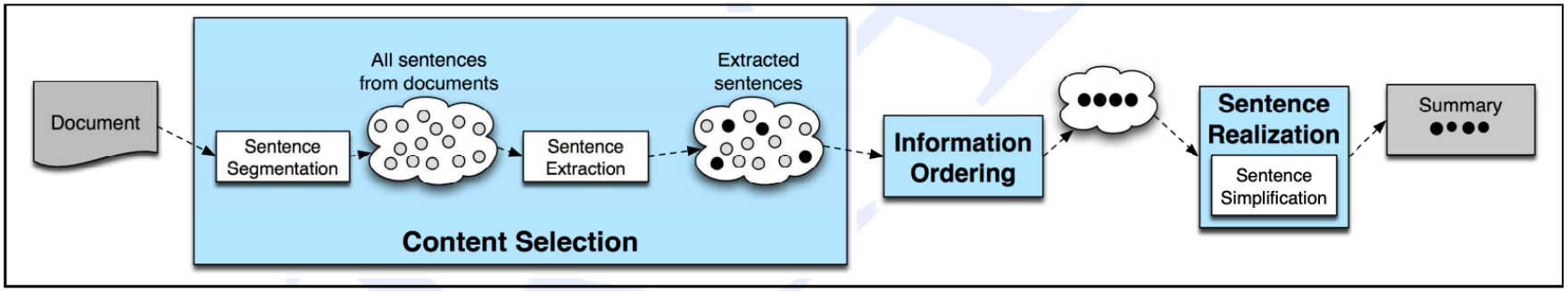


Figure 23.14 The basic architecture of a generic single document summarizer.

Pre-neural **content selection** algorithms:

- Sentence scoring functions can be based on:
  - Presence of topic keywords, computed via e.g. tf-idf
  - Features such as where the sentence appears in the document
- Graph-based algorithms view the document as a set of sentences (nodes), with edges between each sentence pair
  - Edge weight is proportional to sentence similarity
  - Use graph algorithms to identify sentences which are *central* in the graph

Diagram credit: *Speech and Language Processing*, Jurafsky and Martin

Summarization evaluation: ROUGE

ROUGE (Recall-Oriented Understudy for Gisting Evaluation)

$$\text{ROUGE-N} = \frac{\sum_{S \in \{ReferemceSummaries\}} \sum_{gram_n \in S} Count_{match}(gram_n)}{\sum_{S \in \{ReferenceSummaries\}} \sum_{gram_n \in S} Count(gram_n)} \quad (1)$$

Like BLEU, it's based on n-gram overlap. Differences:

- ROUGE has no brevity penalty
- ROUGE is based on recall, while BLEU is based on precision
  - Arguably, precision is more important for MT (then add brevity penalty to fix under-translation), and recall is more important for summarization (assuming you have a max length constraint)
  - However, often a F1 (combination of precision and recall) version of ROUGE is reported anyway.

ROUGE: A Package for Automatic Evaluation of Summaries, Lin, 2004 http://www.aclweb.org/anthology/W04-1013

Summarization evaluation: ROUGE

- BLEU is reported as a single number, which is combination of the precisions for n=1,2,3,4 n-grams
- ROUGE scores are reported separately for each n-gram

- The most commonly-reported ROUGE scores are:
  - ROUGE-1:* unigram overlap
  - ROUGE-2: bigram overlap
  - ROUGE-L: longest common subsequence overlap

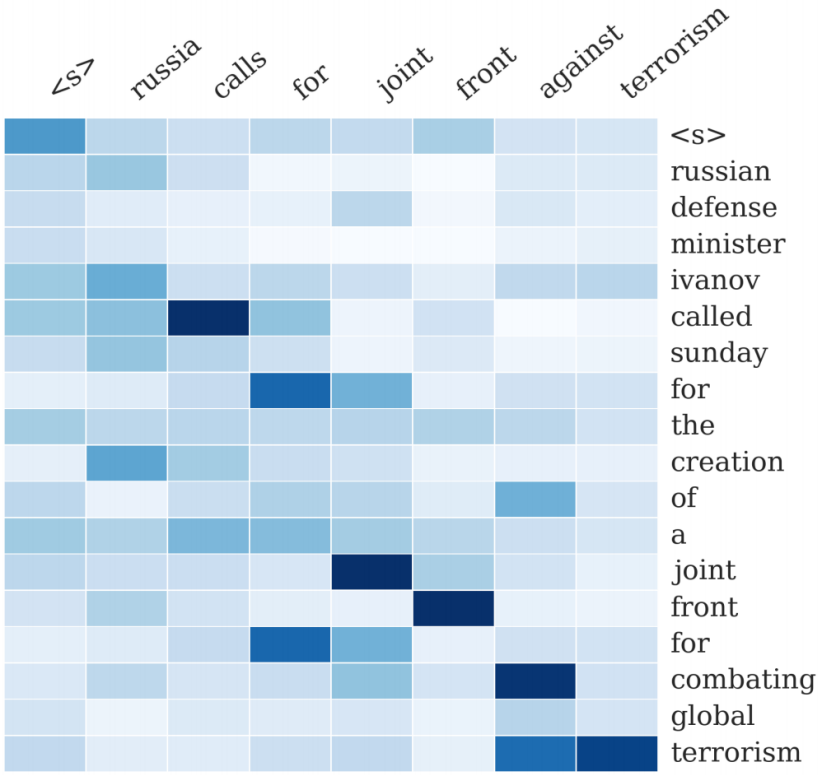
- There is now a convenient Python implementation of ROUGE!
  - https://github.com/pltrdy/rouge

*not to be confused with *ROGUE ONE: A Star Wars Story*

Python implementation of ROUGE: https://github.com/google-research/google-research/tree/master/rouge

Neural summarization (2015 - present)

- 2015: Rush et al. publish the first seq2seq summarization paper
- Single-document abstractive summarization is a translation task!
- Thus we can apply standard seq2seq + attention NMT methods



A Neural Attention Model for Abstractive Sentence Summarization, Rush et al, 2015 https://arxiv.org/pdf/1509.00685.pdf

Neural summarization (2015 - present)

- Since 2015, there have been lots more developments!
  - Making it easier to copy
    - But also preventing too much copying!
  - Hierarchical / multi-level attention
  - More global / high-level content selection
  - Using Reinforcement Learning to directly maximize ROUGE, or other discrete goals (e.g., length)
  - Resurrecting pre-neural ideas (e.g., graph algorithms for content selection) and working them into neural systems
  - …

List of summarization datasets, papers, and codebases: https://github.com/mathsyouth/awesome-text-summarization

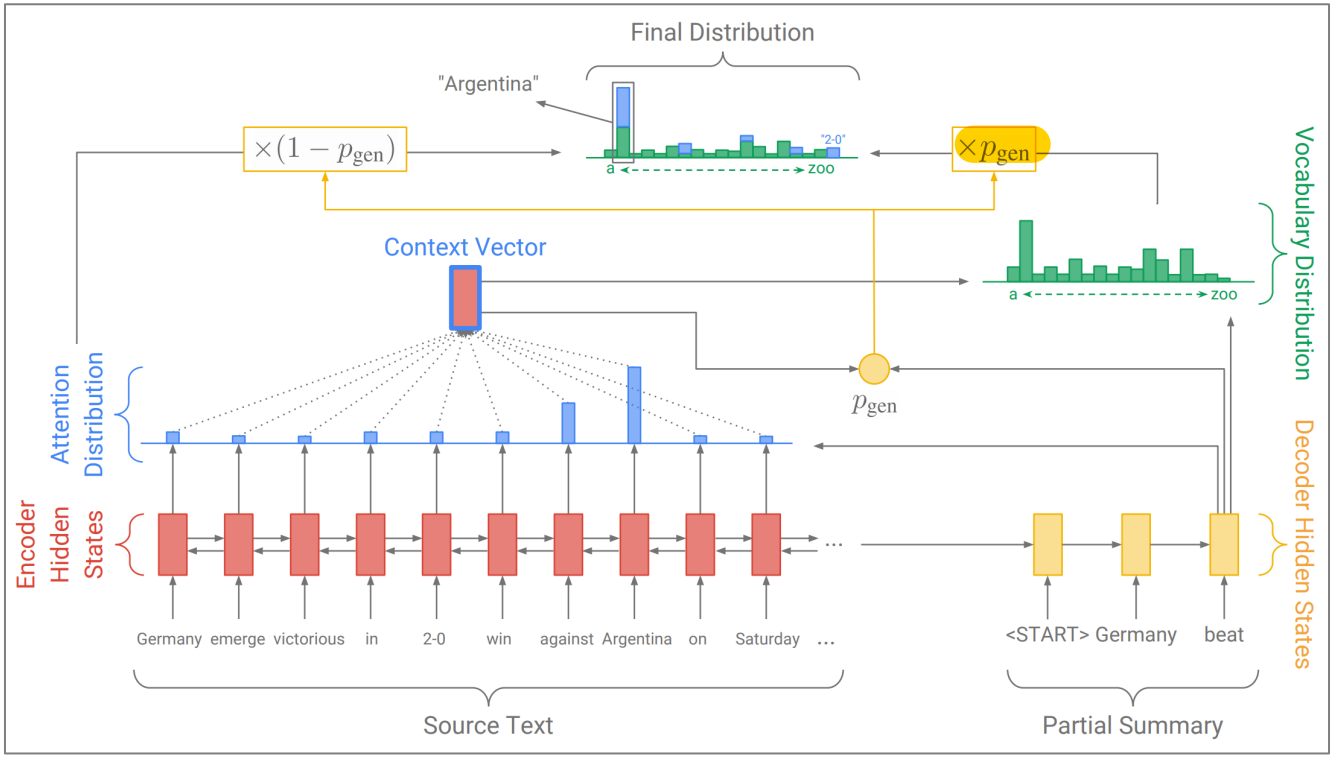
A Survey on Neural Network-Based Summarization Methods, Dong, 2018 https://arxiv.org/pdf/1804.04589.pdf

Neural summarization: copy mechanisms

- Seq2seq+attention systems are good at writing fluent output, but bad at copying over details (like rare words) correctly
- Copy mechanisms use attention to enable a seq2seq system to easily copy words and phrases from the input to the output
  - Clearly this is very useful for summarization
  - Allowing both copying and generating gives us a hybrid extractive/abstractive approach
- There are other papers proposing copy mechanism variants:
  - Language as a Latent Variable: Discrete Generative Models for Sentence Compression, Miao et al, 2016 https://arxiv.org/pdf/1609.07317.pdf
  - Abstractive Text Summarization using Sequence-to-sequence RNNs and Beyond, Nallapati et al, 2016 https://arxiv.org/pdf/1602.06023.pdf
  - Incorporating Copying Mechanism in Sequence-to-Sequence Learning, Gu et al, 2016 https://arxiv.org/pdf/1603.06393.pdf
  - etc.

Neural summarization: copy mechanisms

See et al, 2017, *Get To The Point: Summarization with Pointer-Generator Networks*, https://arxiv.org/pdf/1704.04368.pdf



One example of how to do a copying mechanism:

On each decoder step, calculate p_{gen}, the probability of *generating* the next word (rather than copying it). The final distribution is a mixture of the generation (aka "vocabulary") distribution, and the copying (i.e. attention) distribution:

$$P(w) = p_{\text{gen}} P_{\text{vocab}}(w) + (1 - p_{\text{gen}}) \sum_{i:w_i=w} a_i^t$$

Neural summarization: copy mechanisms

- Big problem with copying mechanisms:
  - **They copy too much!**
    - Mostly long phrases, sometimes even whole sentences
  - What *should* be an abstractive system collapses to a mostly extractive system.

- Another problem:
  - They're bad at overall content selection, especially if the input document is long
  - No overall strategy for selecting content

Neural summarization: better content selection

- Recall: pre-neural summarization had separate stages for **content selection** and **surface realization** (i.e. text generation)

- In a standard seq2seq+attention summarization system, these two stages are mixed in together
  - On each step of the decoder (i.e. surface realization), we do word-level content selection (attention)
  - This is bad: no *global* content selection strategy

- One solution: bottom-up summarization

Bottom-up summarization

- Content selection stage: Use a neural sequence-tagging model to tag words as *include* or *don't-include*
- Bottom-up attention stage: The seq2seq+attention system can't attend to words tagged *don't-include* (apply a mask)

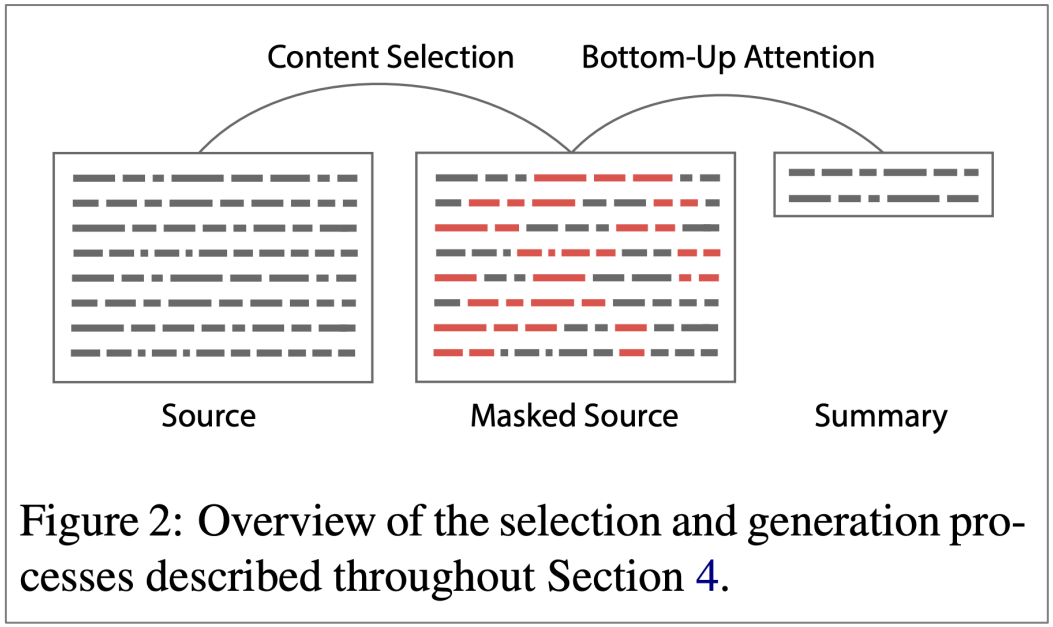


Figure 2: Overview of the selection and generation processes described throughout Section 4.

Simple but effective!

- Better overall content selection strategy
- Less copying of long sequences (i.e. more abstractive output)

Bottom-Up Abstractive Summarization, Gehrmann et al, 2018 https://arxiv.org/pdf/1808.10792v1.pdf

Neural summarization via Reinforcement Learning

- In 2017 Paulus et al published a "deep reinforced" summarization model
- Main idea: Use Reinforcement Learning (RL) to directly optimize ROUGE-L
  - By contrast, standard maximum likelihood (ML) training can't directly optimize ROUGE-L because it's a non-differentiable function
- Interesting finding:
  - Using RL instead of ML achieved higher ROUGE scores, but lower human judgment scores

Model	ROUGE-1	ROUGE-2	ROUGE-L
ML, no intra-attention	44.26	27.43	40.41
ML, with intra-attention	43.86	27.10	40.11
RL, no intra-attention	**47.22**	30.51	**43.27**
ML+RL, no intra-attention	47.03	**30.72**	43.10

Model	Readability	Relevance
ML	6.76	7.14
RL	4.18	6.32
ML+RL	**7.04**	**7.45**

"We observed that our models with the highest ROUGE scores also generated barely-readable summaries."

Overall, a hybrid approach does best!

A Deep Reinforced Model for Abstractive Summarization, Paulus et al, 2017 https://arxiv.org/pdf/1705.04304.pdf

Blog post: https://www.salesforce.com/products/einstein/ai-research/tl-dr-reinforced-model-abstractive-summarization/

Dialogue

"Dialogue" encompasses a large variety of settings:

- **Task-oriented dialogue**
  - Assistive (e.g. customer service, giving recommendations, question answering, helping user accomplish a task like buying or booking something)
  - Co-operative (two agents solve a task together through dialogue)
  - Adversarial (two agents compete in a task through dialogue)
- **Social dialogue**
  - Chit-chat (for fun or company)
  - Therapy / mental wellbeing

Pre- and post-neural dialogue

- Due to the difficulty of open-ended freeform NLG, pre-neural dialogue systems more often used predefined templates, or retrieve an appropriate response from a corpus of responses.

- As in summarization research, since 2015 there have been many papers applying seq2seq methods to dialogue – thus leading to a renewed interest in open-ended freeform dialogue systems

- Some early seq2seq dialogue papers include:
- *A Neural Conversational Model*, Vinyals et al, 2015 https://arxiv.org/pdf/1506.05869.pdf
- *Neural Responding Machine for Short-Text Conversation*, Shang et al, 2015 https://www.aclweb.org/anthology/P15-1152

This is a nice overview of recent (mostly neural) conversational conversational AI work: https://medium.com/gobeyond-ai/a-reading-list-and-mini-survey-of-conversational-ai-32fceea97180

Seq2seq-based dialogue

- However, it quickly became apparent that a naïve application of standard seq2seq+attention methods has serious pervasive deficiencies for (chitchat) dialogue:
  - Genericness / boring responses
  - Irrelevant responses (not sufficiently related to context)
  - Repetition
  - Lack of context (not remembering conversation history)
  - Lack of consistent persona

Irrelevant response problem

- Problem: seq2seq often generates response that's unrelated to user's utterance
  - Either because it's generic (e.g. *"I don't know"*)
  - Or because changing the subject to something unrelated

- One solution: optimize for Maximum Mutual Information (MMI) between input S and response T:

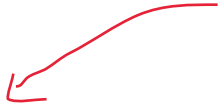
$$\log \frac{p(S,T)}{p(S)p(T)}$$

DISCOURAGE THIS HIGH P(T) ie generic response

$$\hat{T} = \arg\max_{T} \left\{ \log p(T|S) - \log p(T) \right\}$$

A Diversity-Promoting Objective Function for Neural Conversation Models, Li et al, 2016 https://arxiv.org/pdf/1510.03055.pdf

Genericness / boring response problem



- Easy test-time fixes:
  - Directly upweight rare words during beam search
  - Use a sampling decoding algorithm rather than beam search
- Conditioning fixes:
  - Condition the decoder on some additional content (e.g. sample some content words and attend to them)
  - Train a retrieve-and-refine model rather than a generate-from-scratch model
    - i.e. sample an utterance from your corpus of human-written utterances, and edit it to fit the current scenario.
    - This usually produces much more diverse / human-like / interesting utterances!

Why are Sequence-to-Sequence Models So Dull?, Jiang et al, 2018
https://staff.fnwi.uva.nl/m.derijke/wp-content/papercite-data/pdf/jiang-why-2018.pdf

Repetition problem

Simple solution:

- Directly block repeating n-grams during beam search.
  - Usually pretty effective!

More complex solutions:

- Train a coverage mechanism – in seq2seq, this is an objective that prevents the attention mechanism from attending to the same words multiple times.
- Define a training objective to discourage repetition
  - If this is a non-differentiable function of the generated output, then will need some technique like e.g. RL to train

Lack of consistent persona problem

- In 2016, Li et al proposed a seq2seq dialogue model that learns to encode both conversation partners' personas as embeddings
  - The generated utterances are conditioned on the embeddings

- There is now a chitchat dataset called PersonaChat, which includes personas (collections of 5 sentences describing personal traits) for every conversation.
  - This provides a light type of *grounding*, allowing researchers to build persona-conditional dialogue agents

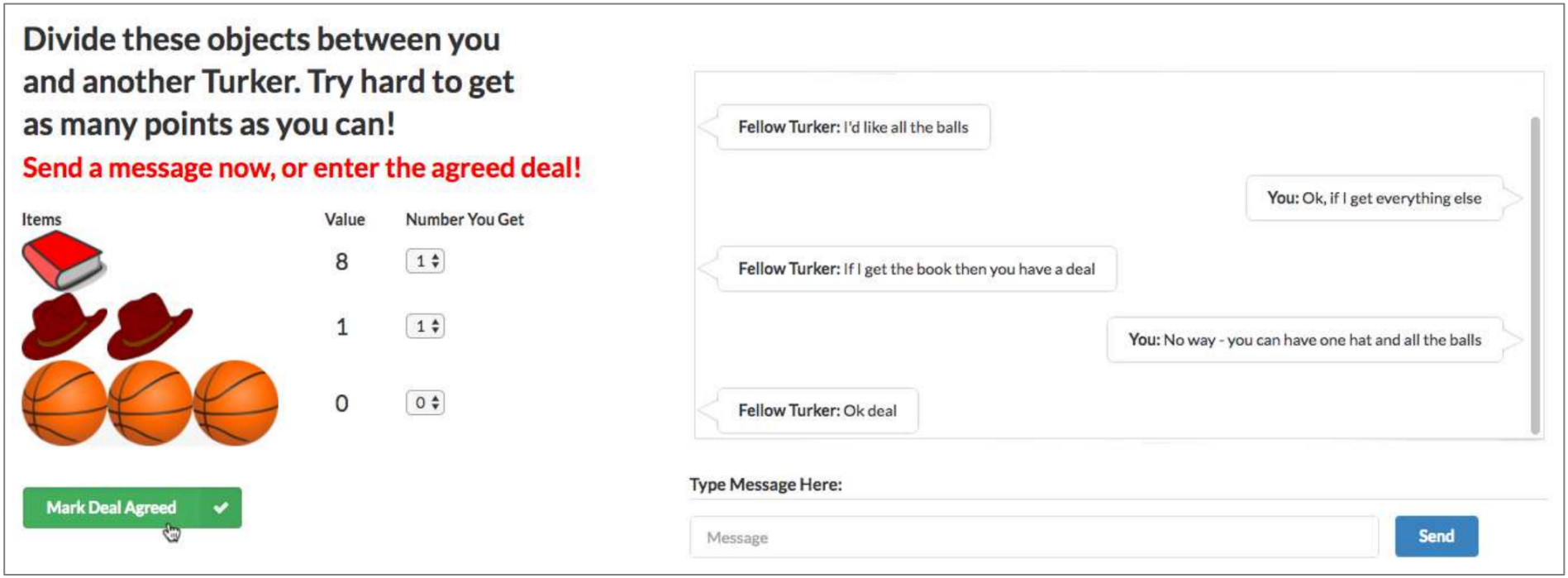
A Persona-Based Neural Conversation Model, Li et al 2016, https://arxiv.org/pdf/1603.06155.pdf

Personalizing Dialogue Agents: I have a dog, do you have pets too?, Zhang et al, 2018 https://arxiv.org/pdf/1801.07243.pdf

Negotiation dialogue

In 2017, Lewis et al collected a negotiation dialogue dataset

- Two agents negotiate (via natural language) how to divide a set of items.
- The agents have different value functions for the items.
- The agents talk until they reach an agreement.



Deal or No Deal? End-to-End Learning for Negotiation Dialogues, Lewis et al, 2017 https://arxiv.org/pdf/1706.05125.pdf

Negotiation dialogue

- They find that training seq2seq systems for the standard maximum likelihood (ML) objective yields fluent but strategically poor dialogue agents.
- Like the Paulus et al summarization paper, they use Reinforcement Learning to optimize for a discrete reward (with the agents playing against themselves during training)
- The RL goal-based objective is combined with the ML objective
- Potential pitfall: If the agents just optimize just the RL goal while playing against each other, they might diverge from English*

*This observation led to an unfortunate media over-reaction: https://www.skynettoday.com/briefs/facebook-chatbot-language/
Deal or No Deal? End-to-End Learning for Negotiation Dialogues, Lewis et al, 2017 https://arxiv.org/pdf/1706.05125.pdf

Negotiation dialogue

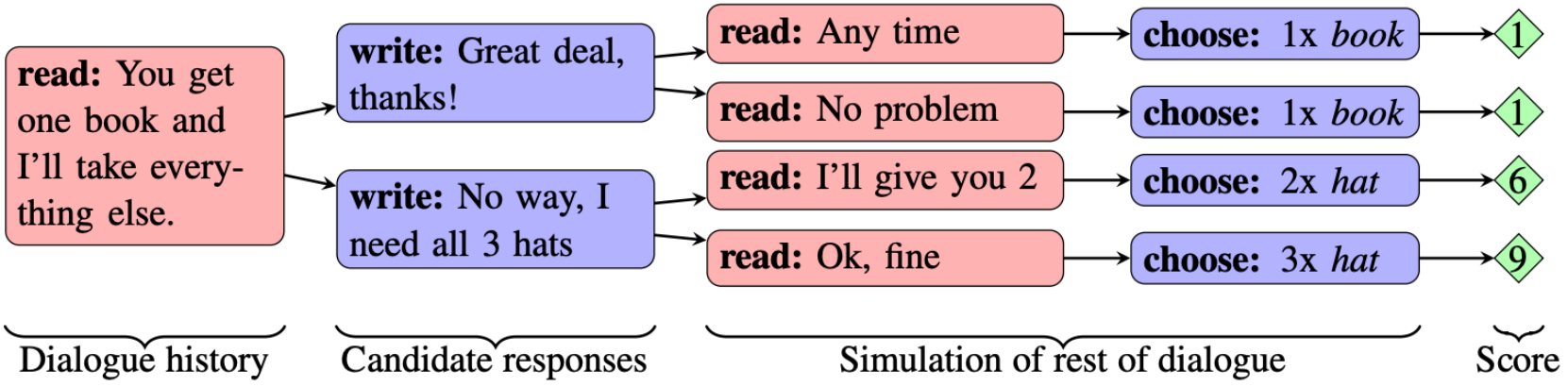


Figure 4: Decoding through rollouts: The model first generates a small set of candidate responses. For each candidate it simulates the future conversation by sampling, and estimates the expected future reward by averaging the scores. The system outputs the candidate with the highest expected reward.

- At test time, the model chooses between possible responses by computing rollouts: simulations of the rest of the conversation and the expected reward.

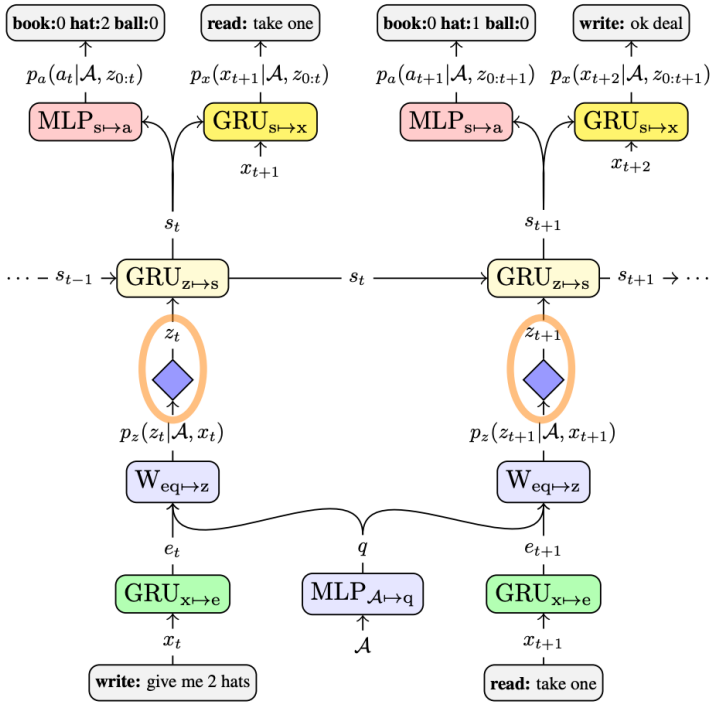
Deal or No Deal? End-to-End Learning for Negotiation Dialogues, Lewis et al, 2017 https://arxiv.org/pdf/1706.05125.pdf

Negotiation dialogue

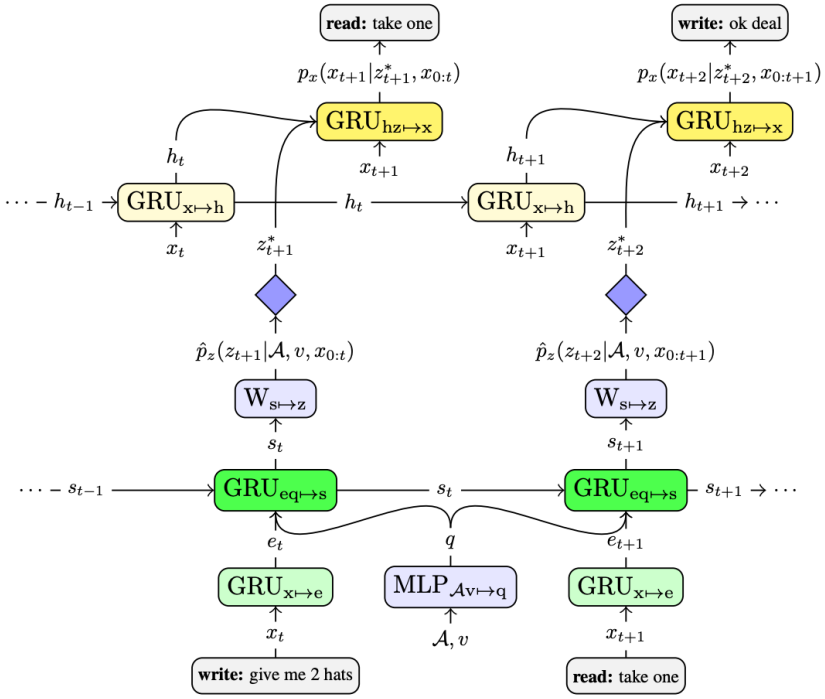
- In 2018, Yarats et al proposed another dialogue model for the negotiation task, that separates the strategic aspect from the NLG aspect.
  - This separation was standard in "old" discourse/dialog NLG approaches
- Each utterance x_t has a corresponding discrete latent variable z_t
- z_t is learned to be a good predictor of future events in the dialogue (future messages, ultimate strategic outcome), but not a predictor of x_t itself
- This means that *"z_t learns to represent x_t's effect on the dialogue, but not the words of x_t"*
- Thus z_t separates the strategic aspect of the task from the NLG aspect. This is useful for controllability, interpretability, easier to learn strategy, etc.

Hierarchical Text Generation and Planning for Strategic Dialogue, Yarats et al, 2018 https://arxiv.org/pdf/1712.05846.pdf

Negotiation dialogue



(a) Clustering Model



(b) Full Model

Figure 3: We pre-train a model to learn a discrete encoder for sentences, which bottlenecks the message x_t through discrete representation z_t (Figure 3a; §5). This architecture forces z_t to capture the most relevant aspects of x_t for predicting future messages and actions. We then extract the learned discrete representations z_t (marked by orange ellipses) and train our full model (Figure 3b): p_x is trained to translate representations z_t^* into messages x_t (§6.1), and $\hat{p}_z$ is trained to predict a distribution over z_t given the dialogue history (§6.2).

Hierarchical Text Generation and Planning for Strategic Dialogue, Yarats et al, 2018 https://arxiv.org/pdf/1712.05846.pdf

Conversational question answering: CoQA

- A new dataset from Stanford NLP!
- Task: answer questions about a piece of text *within the context of a conversation*
- Answers can be abstractive (i.e. not a copied span)
  - But a large percent are spans
- Both a QA / reading-comprehension task, and a dialogue task

Jessica went to sit in her rocking chair. Today was her birthday and she was turning 80. Her granddaughter Annie was coming over in the afternoon and Jessica was very excited to see her. Her daughter Melanie and Melanie's husband Josh were coming as well. Jessica had . . .

Q_1: Who had a birthday?
A_1: Jessica
R_1: Jessica went to sit in her rocking chair. Today was her birthday and she was turning 80.

Q_2: How old would she be?
A_2: 80
R_2: she was turning 80

Q_3: Did she plan to have any visitors?
A_3: Yes
R_3: Her granddaughter Annie was coming over

Q_4: How many?
A_4: Three
R_4: Her granddaughter Annie was coming over in the afternoon and Jessica was very excited to see her. Her daughter Melanie and Melanie's husband Josh were coming as well.

Q_5: Who?
A_5: Annie, Melanie and Josh
R_5: Her granddaughter Annie was coming over in the afternoon and Jessica was very excited to see her. Her daughter Melanie and Melanie's husband Josh were coming as well.

Figure 1: A conversation from the CoQA dataset. Each turn contains a question (Q_i), an answer (A_i) and a rationale (R_i) that supports the answer.

CoQA: a Conversational Question Answering Challenge, Reddy et al, 2018 https://arxiv.org/pdf/1808.07042.pdf

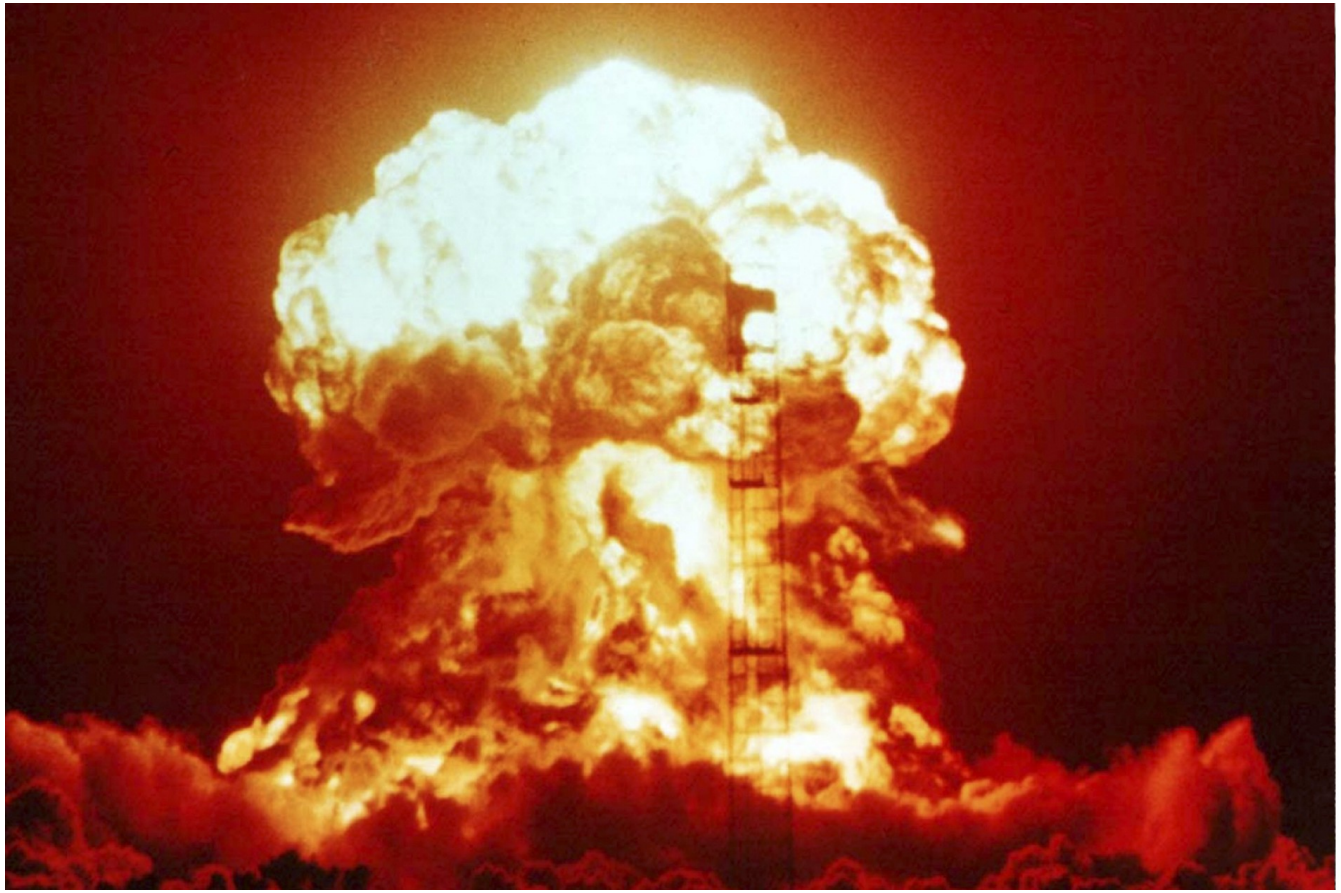
Storytelling

- Most neural storytelling work uses some kind of prompt
  - Generate a story-like paragraph given an image
  - Generate a story given a brief writing prompt
  - Generate the next sentence of a story, given the story so far (*story continuation*)
    - This is different to the previous two, because we are not concerned with the system's performance over several generated sentences

- Neural storytelling is taking off!
  - The first Storytelling Workshop was held in 2018
  - It held a competition (generate a story to accompany a sequence of 5 images)

Storytelling Workshop 2019: http://www.visionandlanguage.net/workshop2019/

Generating a story from an image



Generated story about image
Model: Taylor Swift Lyrics

"You have to be the only light bulb in the night sky, I thought, Oh, God, it 's so dark out of me that I missed you , I promise."

What's interesting here is that this isn't straightforward supervised image-captioning. There was no paired data to learn from.

Generating Stories about Images, https://medium.com/@samim/generating-stories-about-images-d163ba41e4ed

Generating a story from an image

- Question: How to get around the lack of parallel data?
- Answer: Use a common sentence-encoding space

- Skip-thought vectors are a type of general-purpose sentence embedding method
  - The idea is similar to how we learn an embedding for a word by trying to predict the words around it
- Using COCO (an image captioning dataset), learn a mapping from images to the skip-thought encodings of their captions
- Using the target style corpus (Taylor Swift lyrics), train a RNN-LM to decode a skip-thought vector to the original text
- Put the two together

Generating Stories about Images, https://medium.com/@samim/generating-stories-about-images-d163ba41e4ed
Skip-Thought Vectors, Kiros 2015, https://arxiv.org/pdf/1506.06726v1.pdf

Generating a story from a writing prompt

- In 2018, Fan et al released a new story generation dataset collected from Reddit's WritingPrompts subreddit.
- Each story has an associated brief writing prompt.

Prompt: The Mage, the Warrior, and the Priest

Story: A light breeze swept the ground, and carried with it still the distant scents of dust and time-worn stone. The Warrior led the way, heaving her mass of armour and muscle over the uneven terrain. She soon crested the last of the low embankments, which still bore the unmistakable fingerprints of haste and fear. She lifted herself up onto the top the rise, and looked out at the scene before her. [...]

Hierarchical Neural Story Generation, Fan et al, 2018 https://arxiv.org/pdf/1805.04833.pdf

Generating a story from a writing prompt

Fan et al also proposed a complex seq2seq prompt-to-story model:

- It's convolutional-based
  - This makes it faster than RNN-based seq2seq
- Gated multi-head multi-scale self-attention
  - The self-attention is important for capturing long-range context
  - The gates allow the attention mechanism to be more selective
  - The different attention heads attend at different scales – this means there are different attention mechanisms dedicated to retrieving fine-grained information and coarse-grained information
- Model fusion:
  - Pretrain one seq2seq model, then train a *second* seq2seq model that has access to the hidden states of the first
  - The idea is that the first seq2seq model learns general LM and the second learns to condition on the prompt

Hierarchical Neural Story Generation, Fan et al, 2018 https://arxiv.org/pdf/1805.04833.pdf

Generating a story from a writing prompt

The results are impressive!

- Related to prompt
- Diverse; non-generic
- Stylistically dramatic

Example Prompt 1: Aliens start abducting humans

It has been two weeks, and the last of my kind has gone. It is only a matter of time until there will be nothing left. I'm not sure what the hell is going on... I can't think. I can hear a distant scream. I think of a strange, alien sound. I try to speak, but am interrupted by something, something that feels like a drum, I ca not tell. I mean I'm just a little bit older than an average human. But I can, and I can feel the vibrations . I hear the sound of a ship approaching. The ground quakes at the force of the impact, and a loud explosion shatters the silence.

However:

- Mostly atmospheric/descriptive/scene-setting; less events/plot
- When generating for longer, mostly stays on the same idea without moving forward to new ideas – coherence issues

Hierarchical Neural Story Generation, Fan et al, 2018 https://arxiv.org/pdf/1805.04833.pdf

But GPT-2 straight transformer LM output also good!

SYSTEM PROMPT (HUMAN-WRITTEN)	*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.*
MODEL COMPLETION (MACHINE-WRITTEN, 10 TRIES)	The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science. Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved. Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow. Pérez and the others then ventured further into the valley. …

Challenges in storytelling

Stories generated by neural LMs can sound fluent…
but are meandering, nonsensical, with no coherent plot

What's missing?

LMs model *sequences of words*. Stories are *sequences of events*.

- To tell a story, we need to understand and model:
  - Events and the causality structure between them
  - Characters, their personalities, motivations, histories, and relationships to other characters
  - State of the world (who and what is where and why)
  - Narrative structure (e.g. exposition → conflict → resolution)
  - Good storytelling principles (don't introduce a story element then never use it)

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THIS IS INCREDIBLY DIFFICULT

Event2event Story Generation

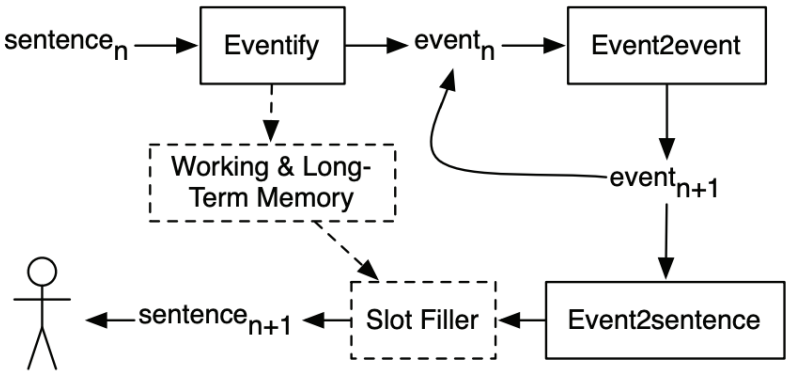


Figure 1: Our automated story generation pipeline. Dashed boxes and arrows represent future work.

Experiment	Input	Extracted Event(s)	Generated Next Event(s)	Generated Next Sentence
All Generalized Events & Generalized Sentence	He reaches out to Remus Lupin, a Defence Against the Dark Arts teacher who is eventually revealed to be a werewolf.	⟨male.n.02, get-13.5.1, ∅, <CHAR>0⟩ ⟨ORGANIZATION, say-37.7-1, monster.n.01, ∅⟩	⟨monster.n.01, amuse-31.1, sarge, ∅⟩ ⟨monster.n.01, amuse-31.1, realize, ∅⟩ ⟨monster.n.01, conjecture-29.5-1, ∅, ∅⟩ ⟨male.n.02, conduit.n.01, entity.n.01, ∅⟩ ⟨male.n.02, free-80-1, ∅, penal_institution.n.01⟩	When monster.n.01 nemesis.n.01 describes who finally realizes male.n.02 can not, dangerous entity.n.01 male.n.02 is released from penal_institution.n.01.

Event Representations for Automated Story Generation with Deep Neural Nets, Martin et al, 2018
https://www.aaai.org/ocs/index.php/AAAI/AAAI18/paper/view/17046/15769

Structured Story Generation

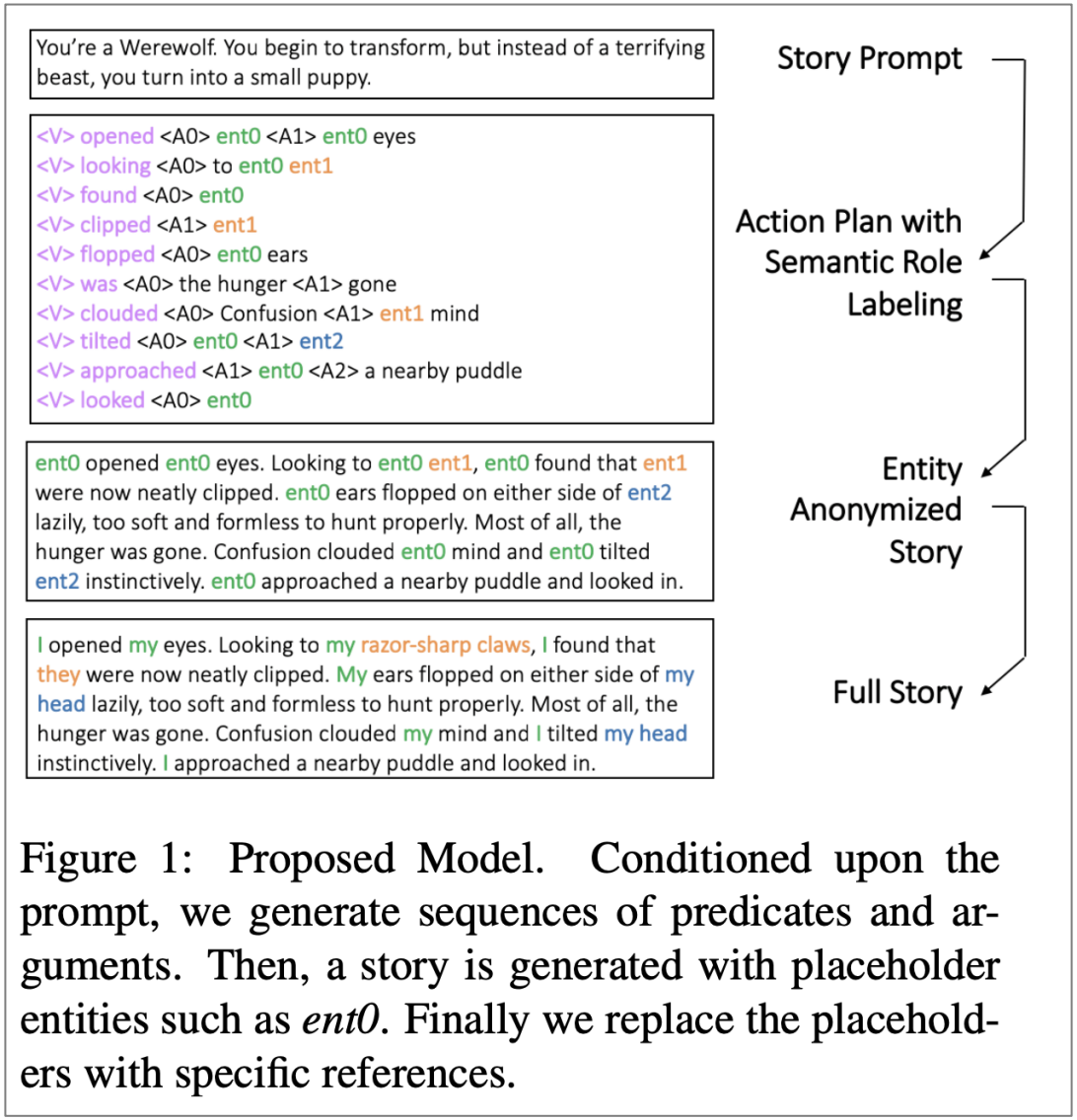


Figure 1: Proposed Model. Conditioned upon the prompt, we generate sequences of predicates and arguments. Then, a story is generated with placeholder entities such as *ent0*. Finally we replace the placeholders with specific references.

Strategies for Structuring Story Generation, Fan et al, 2019 https://arxiv.org/pdf/1902.01109.pdf

Tracking events, entities, state, etc.

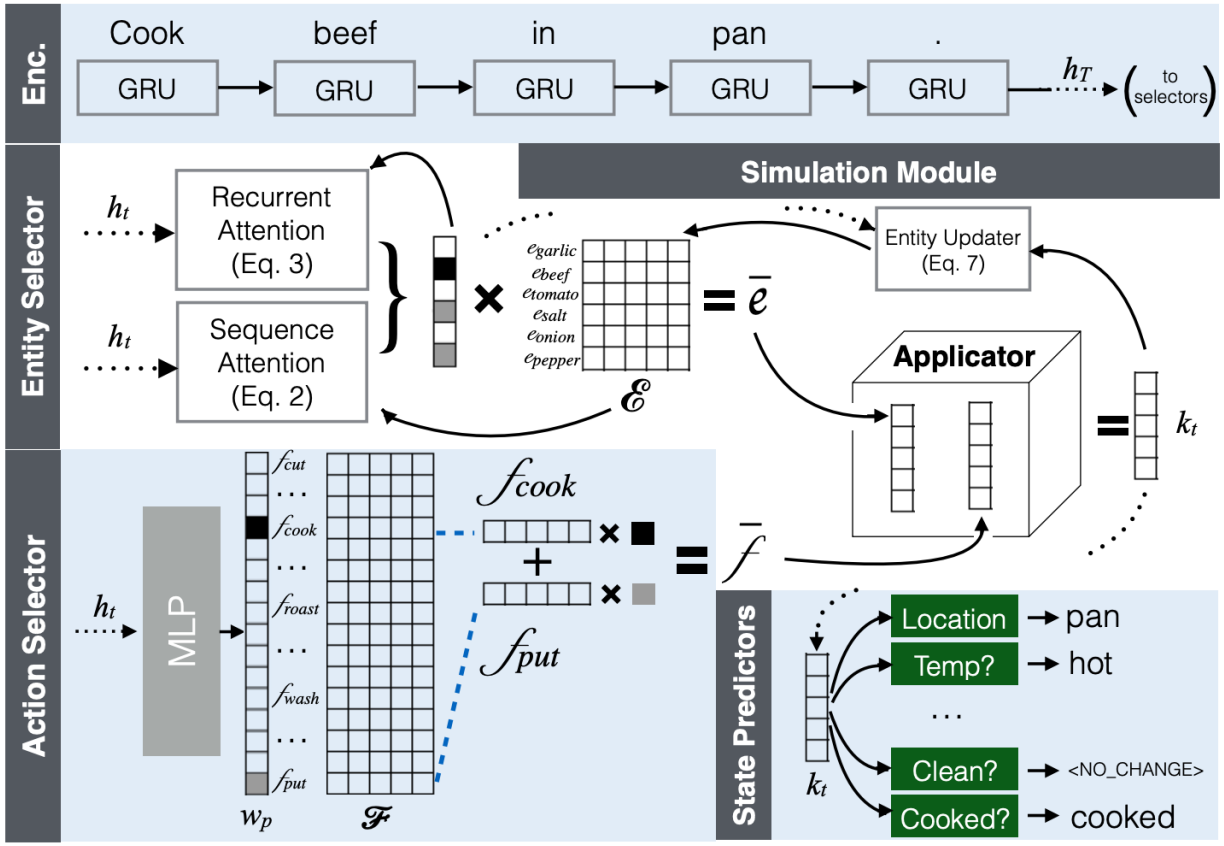
- Sidenote: there's been lots of work on tracking events/ entities/state in neural NL**U** (natural language **understanding**)
  - For example, Yejin Choi's group* does lots of work in this area

- Applying these methods to NLG is even more difficult
  - It's more manageable if you narrow the scope:
  - Instead of generating open-domain natural language stories while tracking state…
  - generate a recipe (given the ingredients) while tracking the state of the ingredients!

*Yejin Choi research group: https://homes.cs.washington.edu/~yejin/

Tracking world state while generating a recipe

- Neural Process Network: generates recipe instructions, given the ingredients
- Explicitly tracks the state of all the ingredients, and uses this to decide what action to take next.



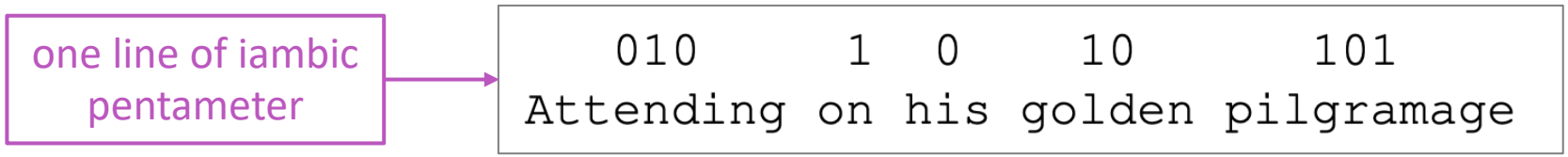
Simulating Action Dynamics with Neural Process Networks, Bosselut et al, 2018 https://arxiv.org/pdf/1711.05313.pdf

Poetry generation: Hafez

- Hafez: a poetry generation system by Ghazvininejad et al
- Main idea: Use a Finite State Acceptor (FSA) to define all possible sequences that obey the desired rhythm constraints. Then use the FSA to constrain the output of a RNN-LM.

For example:

- A Shakespearean sonnet is 14 lines of iambic pentameter



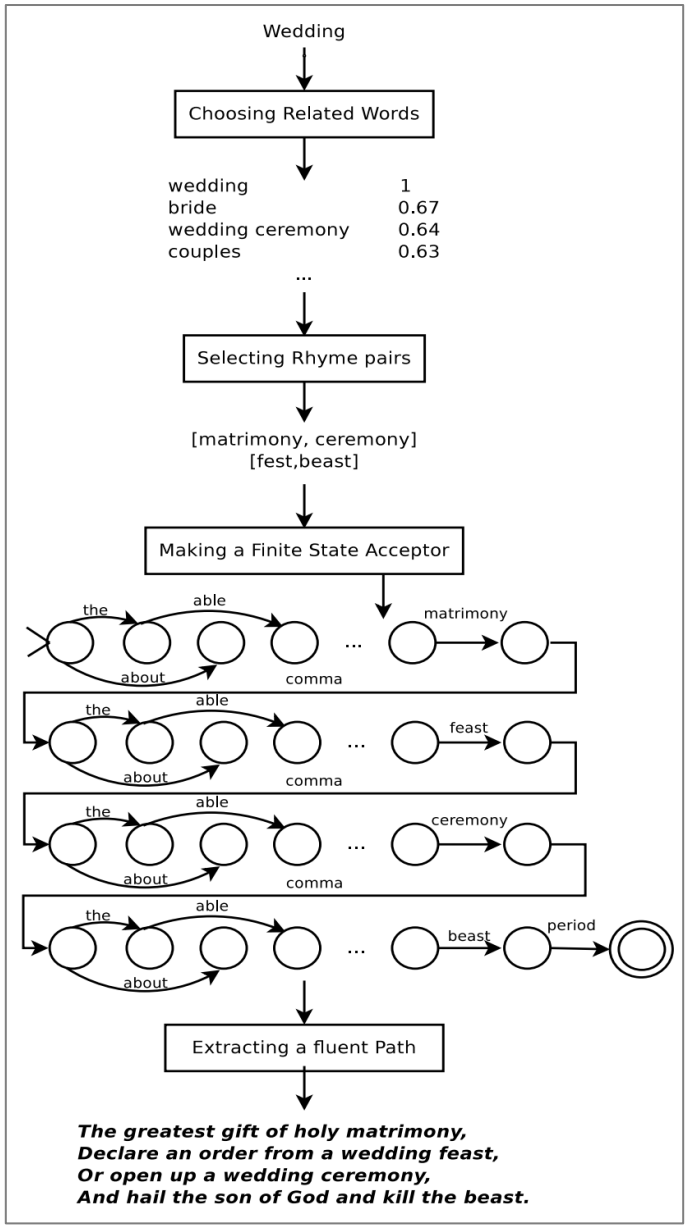
- So the Shakespearean sonnet FSA is $((01)^5)^{14}$
- During beam search decoding, only explore hypotheses that fall within the FSA.

Generating Topical Poetry, Ghazvininejad et al, 2016 http://www.aclweb.org/anthology/D16-1126

Hafez: an Interactive Poetry Generation System, Ghazvininejad et al, 2017 http://www.aclweb.org/anthology/P17-4008

Poetry generation: Hafez

- Full system:
- User provides topic word
- Get a set of words related to topic
- Identify rhyming topical words. These will be the ends of each line
- Generate the poem using RNN-LM constrained by FSA
- The RNN-LM is *backwards* (right-to-left). This is necessary because last word of each line is fixed.



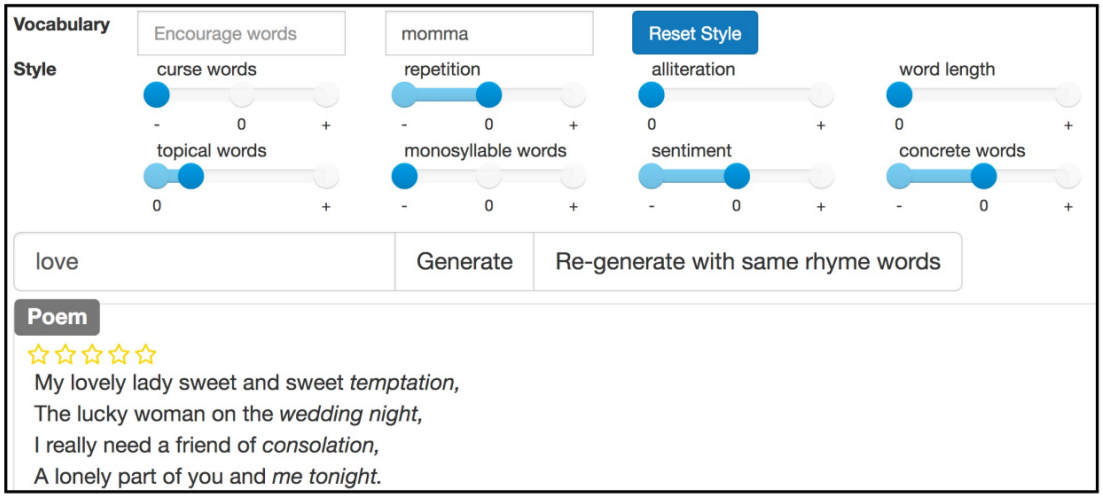
Generating Topical Poetry, Ghazvininejad et al, 2016 http://www.aclweb.org/anthology/D16-1126

Hafez: an Interactive Poetry Generation System, Ghazvininejad et al, 2017 http://www.aclweb.org/anthology/P17-4008

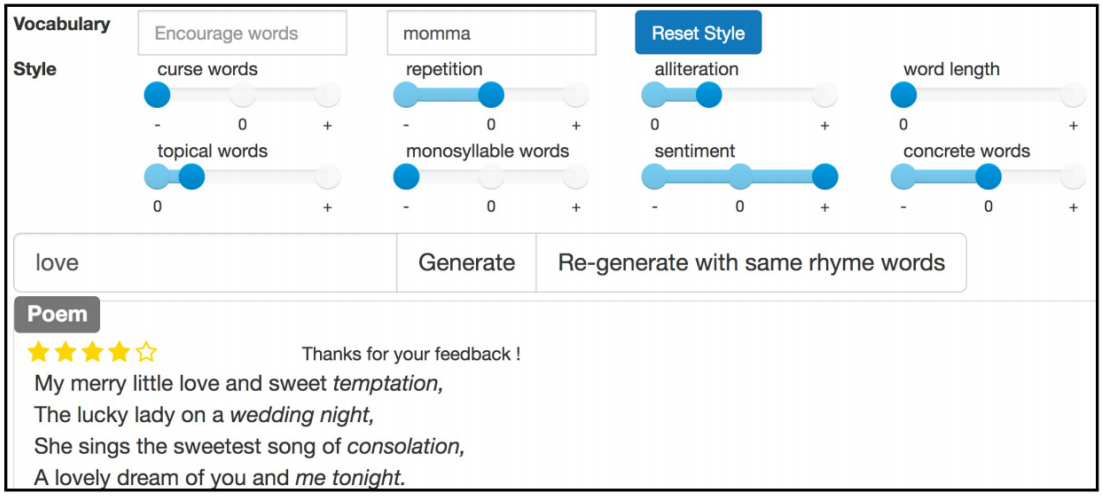
Poetry generation: Hafez

In a follow-up paper, the authors made the system interactive and user-controllable.

The control method is simple: during beam search, upweight the scores of words that have the desired features.



(a) Poem generated with default style settings



(b) Poem generated with user adjusted style settings

Generating Topical Poetry, Ghazvininejad et al, 2016 http://www.aclweb.org/anthology/D16-1126

Hafez: an Interactive Poetry Generation System, Ghazvininejad et al, 2017 http://www.aclweb.org/anthology/P17-4008

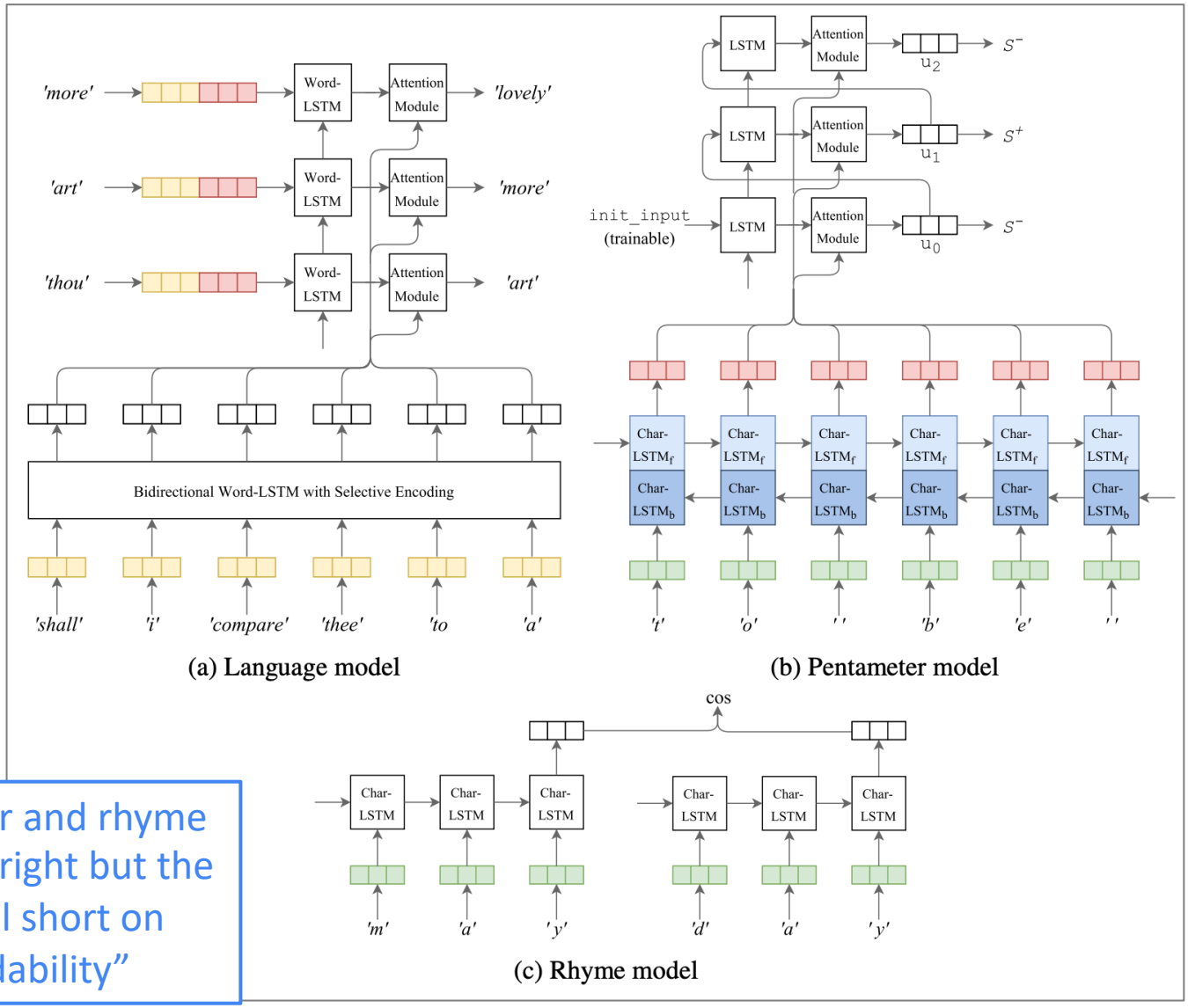
Poetry generation: Deep-speare

A more end-to-end approach to poetry generation (Lau et al)

Three components:

- language model
- pentameter model
- rhyme model

… learned jointly as a multi-task learning problem



Authors find that meter and rhyme is relatively easy to get right but the generated poems fall short on "emotion and readability"

Deep-speare: A joint neural model of poetic language, meter and rhyme, Lau et al, 2018 http://aclweb.org/anthology/P18-1181

Non-autoregressive generation for NMT

- In 2018, Gu et al published a "Non-autoregressive Neural Machine Translation" model
  - Meaning: it *does not* generate the translation left-to-right, with each word depending on the ones before.

- It generates the translation in parallel!

- This has obvious efficiency advantages, but is also intriguing from a text generation point of view.

- The architecture is Transformer-based; the big difference is that the decoder can run in parallel *at test time*.

Non-Autoregressive Neural Machine Translation, Gu et al, 2018 https://arxiv.org/pdf/1711.02281.pdf

Non-autoregressive generation for NMT

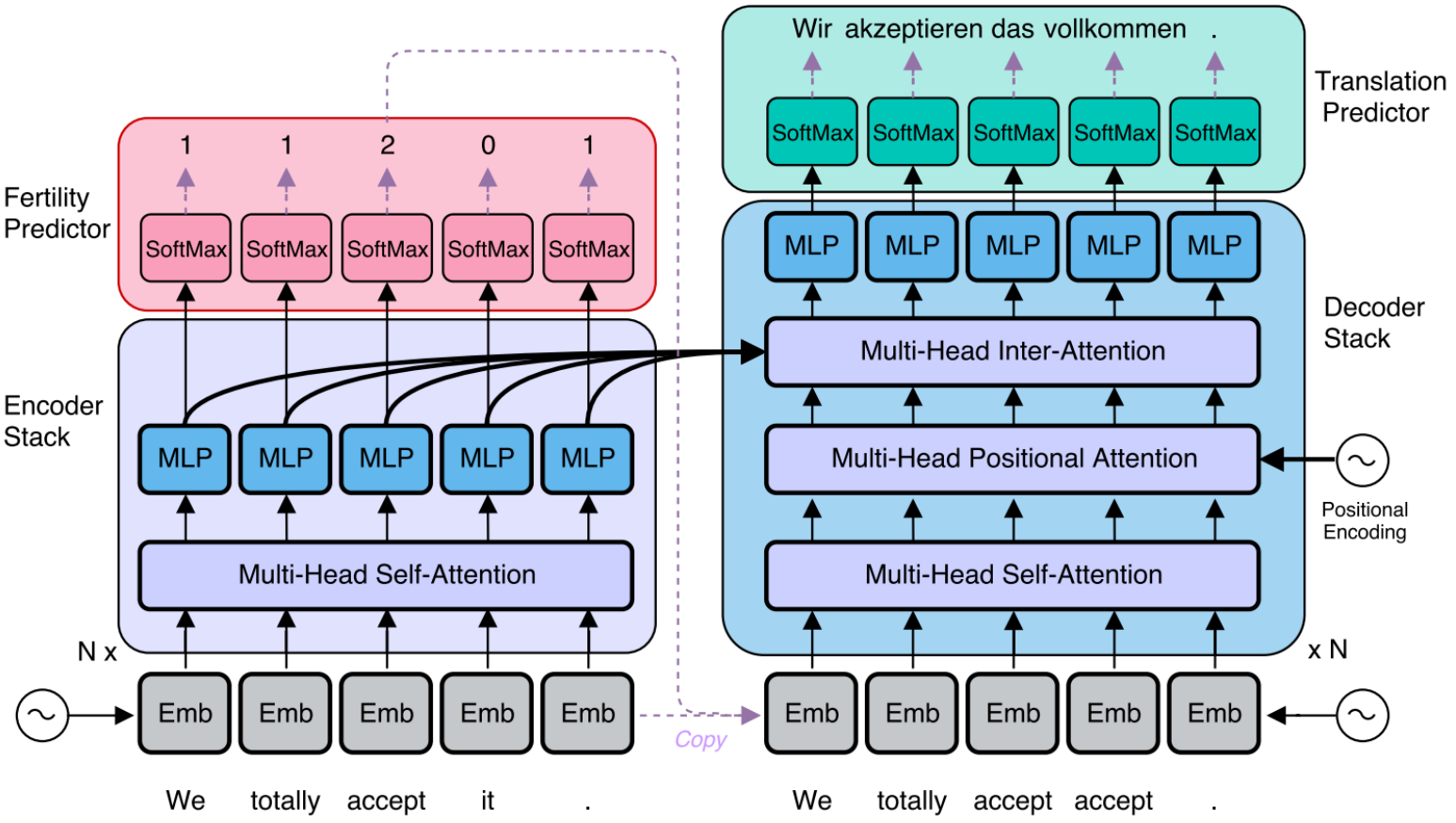


Figure 2: The architecture of the NAT, where the black solid arrows represent differentiable connections and the purple dashed arrows are non-differentiable operations. Each sublayer inside the encoder and decoder stacks also includes layer normalization and a residual connection.

Non-Autoregressive Neural Machine Translation, Gu et al, 2018 https://arxiv.org/pdf/1711.02281.pdf

Section 3:
NLG evaluation

Automatic evaluation metrics for NLG

Word overlap based metrics (BLEU, ROUGE, METEOR, F1, etc.)

- We know that they're not ideal for machine translation
- They're much worse for summarization, which is more open-ended than machine translation
  - Unfortunately, ROUGE also typically rewards extractive summarization systems more than abstractive systems
- And they're much, much worse for dialogue, which is more open-ended that summarization.
  - Similarly for, e.g., story generation

Word overlap metrics are not good for dialogue

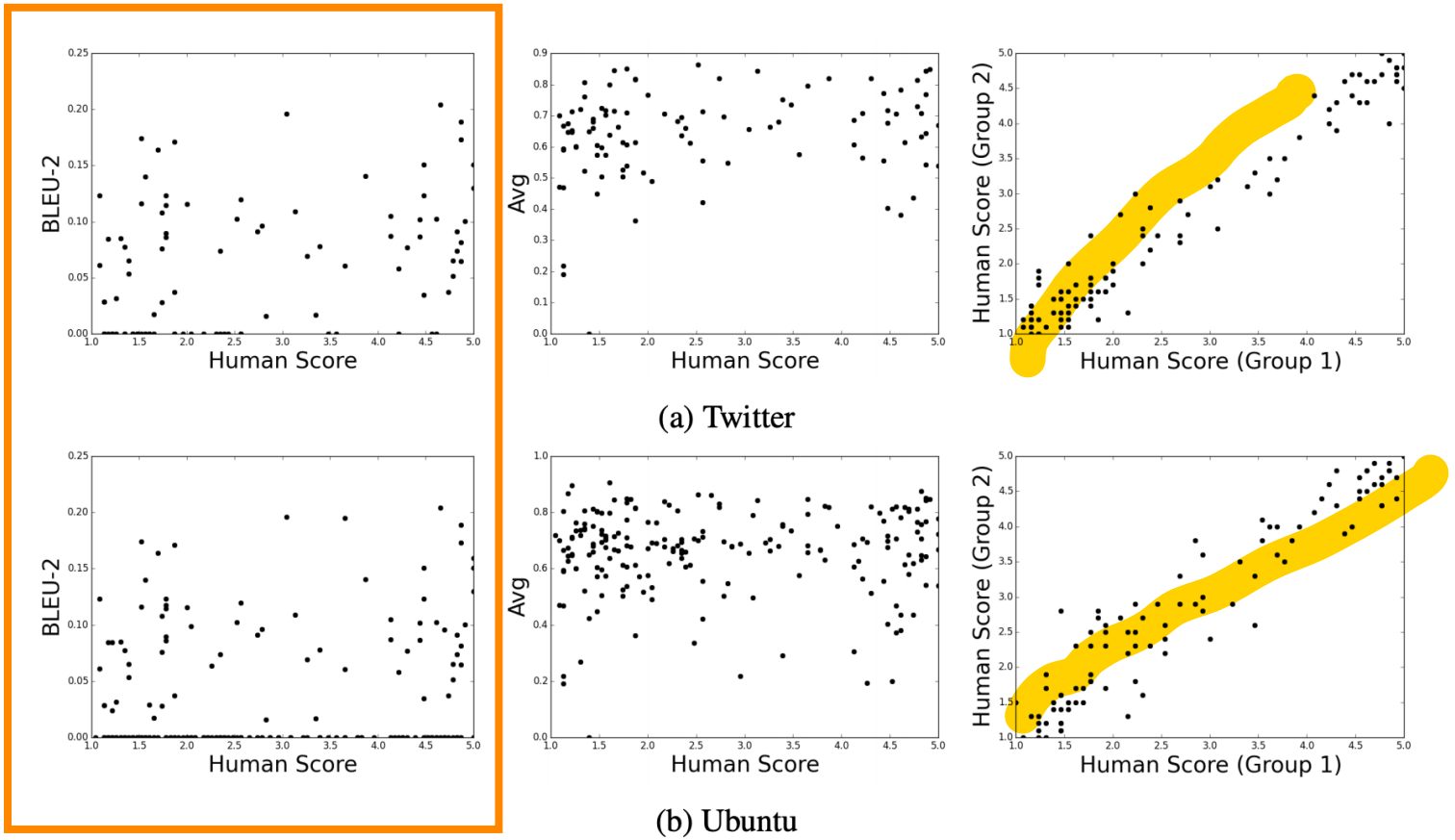
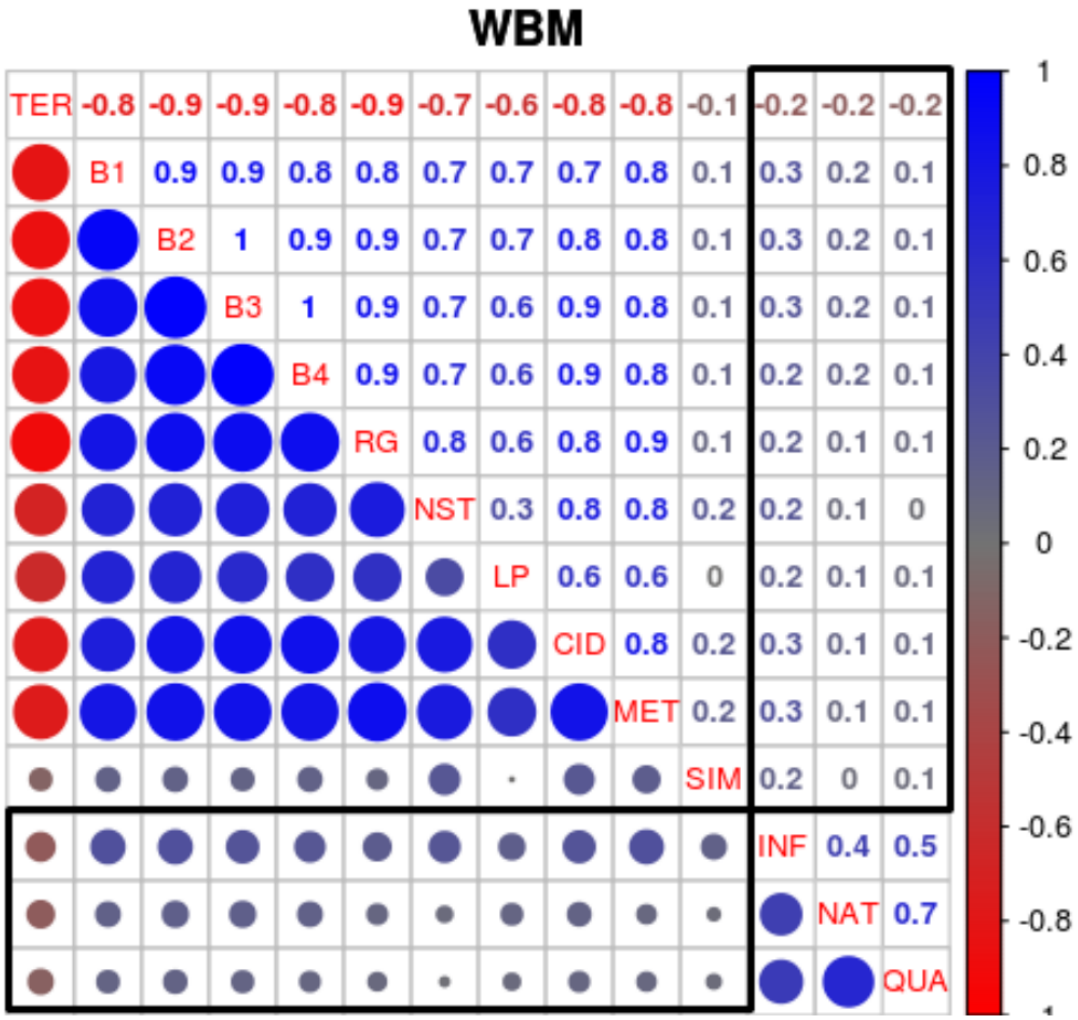


Figure 1: Scatter plots showing the correlation between metrics and human judgements on the Twitter corpus (a) and Ubuntu Dialogue Corpus (b). The plots represent BLEU-2 (left), embedding average (center), and correlation between two randomly selected halves of human respondents (right).

How NOT To Evaluate Your Dialogue System: An Empirical Study of Unsupervised Evaluation Metrics for Dialogue Response Generation, Liu et al, 2017 https://arxiv.org/pdf/1603.08023.pdf

Word overlap metrics are not good for dialogue



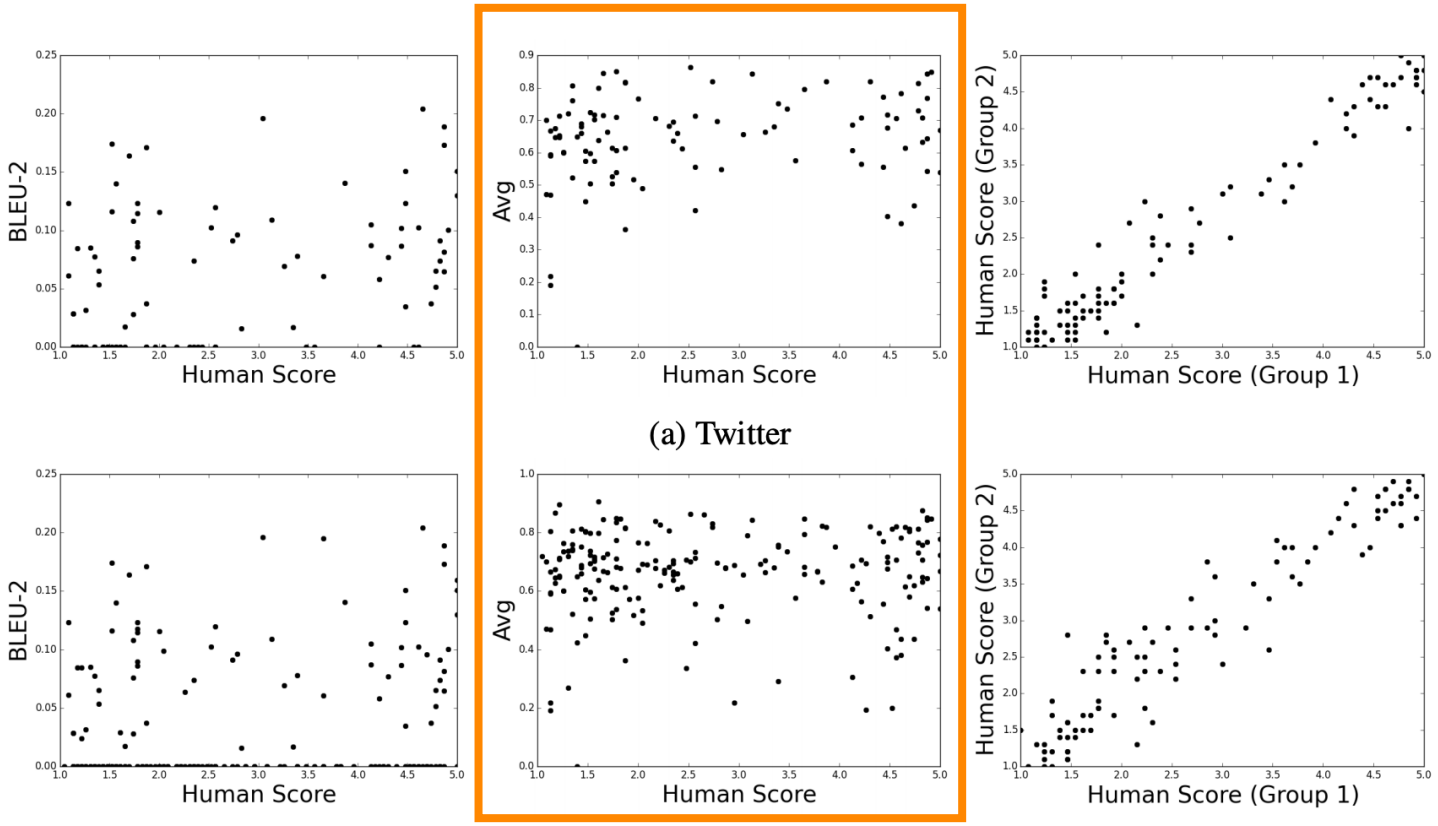
Why We Need New Evaluation Metrics for NLG, Novikova et al, 2017 https://arxiv.org/pdf/1707.06875.pdf

Automatic evaluation metrics for NLG

- What about perplexity?
  - Captures how powerful your LM is, but doesn't tell you anything about generation (e.g. if your decoding algorithm is bad, perplexity is unaffected)

- Word embedding based metrics?
  - Main idea: compare the similarity of the word embeddings (or average of word embeddings), not just the overlap of the words themselves. Captures semantics in a more flexible way.
  - Unfortunately, still doesn't correlate well with human judgments for open-ended tasks like dialogue.

Word overlap metrics are not good for dialogue



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Automatic evaluation metrics for NLG

- We have no automatic metrics to adequately capture overall quality (i.e. a proxy for human quality judgment).

- But we can define more focused automatic metrics to capture particular aspects of generated text:
  - Fluency (compute probability w.r.t. well-trained LM)
  - Correct style (prob w.r.t. LM trained on target corpus)
  - Diversity (rare word usage, uniqueness of n-grams)
  - Relevance to input (semantic similarity measures)
  - Simple things like length and repetition
  - Task-specific metrics e.g. compression rate for summarization
- Though these don't measure overall quality, they can help us track some important qualities that we care about.

Human evaluation

- Human judgments are regarded as the **gold standard**
- Of course, we know that human eval is slow and expensive
- …but are those the only problems?
- Supposing you do have access to human evaluation:
  Does human evaluation solve all of your problems?

- **No!**
- Conducting human evaluation effectively is very difficult
- Humans:
  - are inconsistent
  - can be illogical
  - lose concentration
  - misinterpret your question
  - can't always explain why they feel the way they do

Detailed human eval of controllable chatbots

- Results from working on a chatbot project (PersonaChat):
- Investigated controllability (in particular, controlling aspects of the generated utterances such as repetition, specificity, response-relatedness and question-asking).

Input: *Yes, I'm studying law at the moment*
Baseline Response: *That sounds like a lot of fun!*

(a)	NIDF	Weighted Decoding Response
	0.6%	*Oh.....*
	17.1%	*That sounds like a lot of fun!*
	18.3%	*That sounds like a lot of fun. How long have you been studying?*
	38.5%	*I majored in practising my spiritual full time philosophy test*
	71.9%	*Oh wow! Merna jean isa paino yi hao hui bu acara sya gila* [. . .]

Controlling specificity

Input: *Do you go get coffee often*
Baseline Response: *I do, when I am not playing the piano.*

Wt	Sim	Weighted Decoding Response
-10.0	-0.05	*I am a musician.*
-5.0	-0.02	*I do, when I am not playing the piano.*
0.0	-0.02	*I do, when I am not playing the piano.*
5.0	0.40	*I do, usually at starbucks.*
8.0	0.59	*Not usually, especially when you drink latte.*
11.0	0.72	*Not often, usually with drinks, espresso, latte, tea, etc.*

Controlling response-relatedness

sweet spot

What makes a good conversation? How controllable attributes affect human judgments, See et al, 2019 https://arxiv.org/pdf/1902.08654.pdf

Detailed human eval of controllable chatbots

- How to ask for human quality judgments?
- Idea: simple overall quality (multiple-choice) questions like:
  - *How well did this conversation go?*
  - *How engaging was this user?*
  - *Which of these users gave a better response?*
  - *Would you want to talk to this user again?*
  - *Do you think this user is a human or a bot?*
- **Major problems**:
  - Necessarily very subjective
  - Respondents have different expectations; this affects their judgments
  - Catastrophic misunderstanding of the question (e.g. *"the chatbot was very engaging because it always wrote back"*)
  - Overall quality depends on many underlying factors; how should they be weighed and/or compared?

What makes a good conversation? How controllable attributes affect human judgments, See et al, 2019 https://arxiv.org/pdf/1902.08654.pdf

Detailed human eval of controllable chatbots

Possible solution: design a detailed human evaluation system that separates out the important factors that contribute to overall chatbot quality:

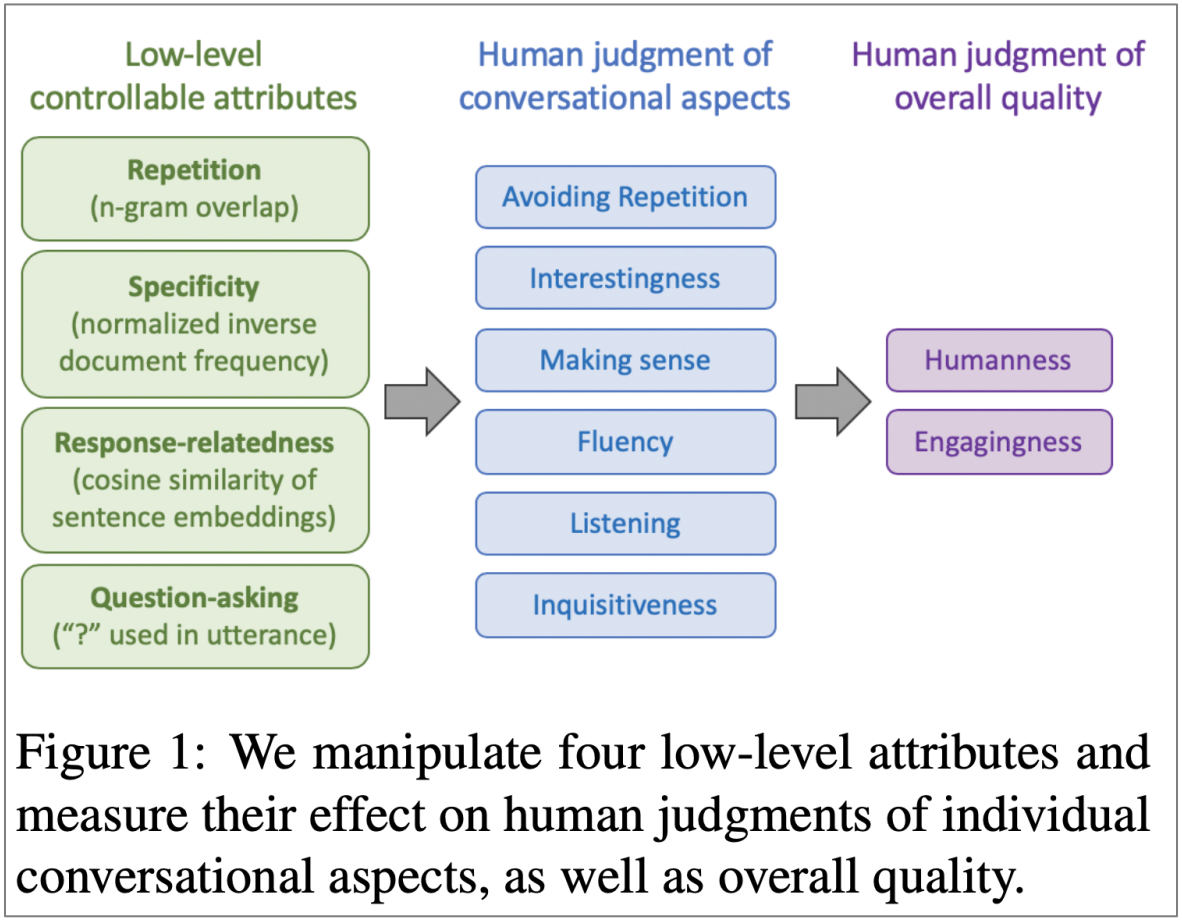

Figure 1: We manipulate four low-level attributes and measure their effect on human judgments of individual conversational aspects, as well as overall quality.

What makes a good conversation? How controllable attributes affect human judgments, See et al, 2019 https://arxiv.org/pdf/1902.08654.pdf

Detailed human eval of controllable chatbots

Findings:

- Controlling repetition is extremely important for all human judgments
- Asking more questions improves engagingness
- Controlling specificity (less generic utterances) improves engagingness, interestingness and perceived listening ability of the chatbot.
  - However, human evaluators have a low tolerance for the risks (e.g. nonsensical or non-fluent output) associated with the less generic bot

- The overall metric "engagingness" (i.e. enjoyment) is easy to maximize – our bots reached near-human performance
- The overall metric "humanness" (i.e. Turing test) is not at all easy to maximize – all bots are far below human performance

- Humanness is not the same as conversational quality!
- Humans are suboptimal conversationalists: they scored poorly on interestingness, fluency, listening, and asked too few questions.

What makes a good conversation? How controllable attributes affect human judgments,
See et al, 2019 https://arxiv.org/pdf/1902.08654.pdf

Possible new avenues for NLG eval?

- Corpus-level metrics
  - Should an eval metric be applied to each example in the test set independently, or a function of the whole corpus?
  - e.g. if a dialogue model always gives the same generic answer to every example in the test set, it should be penalized
- Eval metrics that measure the diversity-safety tradeoff
- Human eval for free
  - Gamification: make the task (e.g. talking to a chatbot) fun, so humans provide supervision and implicit evaluation for free
- Adversarial discriminator as an evaluation metric
  - Test whether the NLG system can fool a discriminator which is trained to distinguish human text from artificially generated text

Section 4:
Thoughts on NLG research, current trends, and the future

Exciting current trends in NLG

- Incorporating discrete latent variables into NLG
  - May help with modeling structure in tasks that really need it, like storytelling, task-oriented dialogue, etc
- Alternatives to strict left-to-right generation
  - Parallel generation, iterative refinement, top-down generation for longer pieces of text
- Alternative to maximum likelihood training with teacher forcing
  - More holistic sentence-level (rather than word-level) objectives

NLG research: Where are we? Where are we going?

- ~5 years ago, NLP + Deep Learning research was a wild west

- Now, it's a lot less wild
- …but NLG seems like one of the wildest parts remaining

Image credit: mstodt on Pixabay

Neural NLG community is rapidly maturing

- During the early years of NLP + Deep Learning, community was mostly transferring successful NMT methods to NLG tasks.
- Now, increasingly more inventive NLG techniques emerging, specific to *non-NMT* generation settings.
- Increasingly more (neural) NLG workshops and competitions, especially focusing on open-ended NLG:
  - NeuralGen workshop
  - Storytelling workshop
  - Alexa Prize: https://developer.amazon.com/alexaprize
  - ConvAI2 NeurIPS challenge
- These are particularly useful to organize the community, increase reproducibility, standardize eval, etc.
- The biggest roadblock for progress is eval

8 things we've learned from working in NLG

1. The more open-ended the task, the harder everything becomes.
   - Constraints are sometimes welcome!

2. Aiming for a specific improvement can be more manageable than aiming to improve overall generation quality.

3. If you're using an LM for NLG: improving the LM (i.e. perplexity) will most likely improve generation quality.
   - ...but it's not the only way to improve generation quality.

4. Look at your output, a lot

8 things we've learned from working in NLG

5. You need an automatic metric, even if it's imperfect.
   - You probably need *several* automatic metrics.

6. If you do human eval, make the questions as focused as possible.

7. Reproducibility is a huge problem in today's NLP + Deep Learning, and a huger problem in NLG.
   - Please, publicly release all your generated output along with your paper!

8. Working in NLG can be very frustrating. But also very funny…

Bizarre conversations with my chatbot

```
Enter Your Message:  what's your biggest secret?
[Seq2Seq]: i'm the reincarnation of satan
```

```
Enter Your Message: would you say you're an adventurous person?
[Seq2Seq]: i try to be
Enter Your Message: what's the craziest thing you've ever done?
[Seq2Seq]: i really like waffles
```

```
Enter Your Message: how many legs do you have?
[Seq2Seq]: all my limbs are covered in my armpits
```

```
Enter Your Message: can i tell you a joke?
[Seq2Seq]: sure why not ?
Enter Your Message: why did the chicken cross the road?
[Seq2Seq]: because it was severed
Enter Your Message: why would you say something like that?
[Seq2Seq]: because it was severed
```

```
Enter Your Message: What's the best erogenous zone?
[Seq2Seq]: the safest option is dungeons and dragons
```