Computational Argumentation — Part VI

Argument Generation

Henning Wachsmuth

https://ai.uni-hannover.de

Natural Language Processing

Leibniz
Universität
Hannover

Learning goals

- **Concepts**
  - Selected basic concepts of natural language generation
  - Views of core building blocks of an argument
  - Distinction of content and style in general and in text

https://commons.wikimedia.org

- **Methods**
  - Extractive and abstractive summarization of argumentative texts
  - Knowledge-based and neural composition and creation of arguments
  - Neural language models for rewriting and countering arguments

https://pixabay.com

- **Associated research fields**
  - Natural language processing

https://pixabay.com

- **Within this course**
  - How to reuse mined and assessed arguments in new arguments and how create fully new arguments

Outline: Introduction

I. Introduction to computational argumentation

II. Basics of natural language processing

III. Basics of argumentation

IV. Argument mining

V. Argument assessment

VI. Argument generation

VII. Applications of computational argumentation

VIII. Conclusion

a) Introduction

b) Argument summarization

c) Argument composition and creation

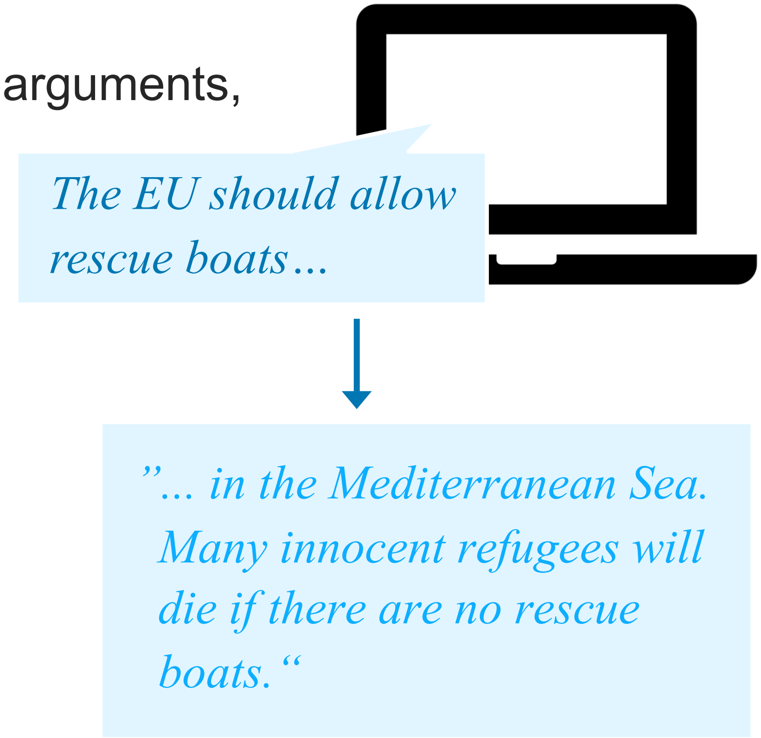
d) Argument rewriting and countering

e) Conclusion

Argument generation

- **Argument generation**
  - The synthesis of new argumentative units, arguments, and argumentative texts

    We use *synthesis* and *generation* largely interchangeably here.



The EU should allow rescue boats…

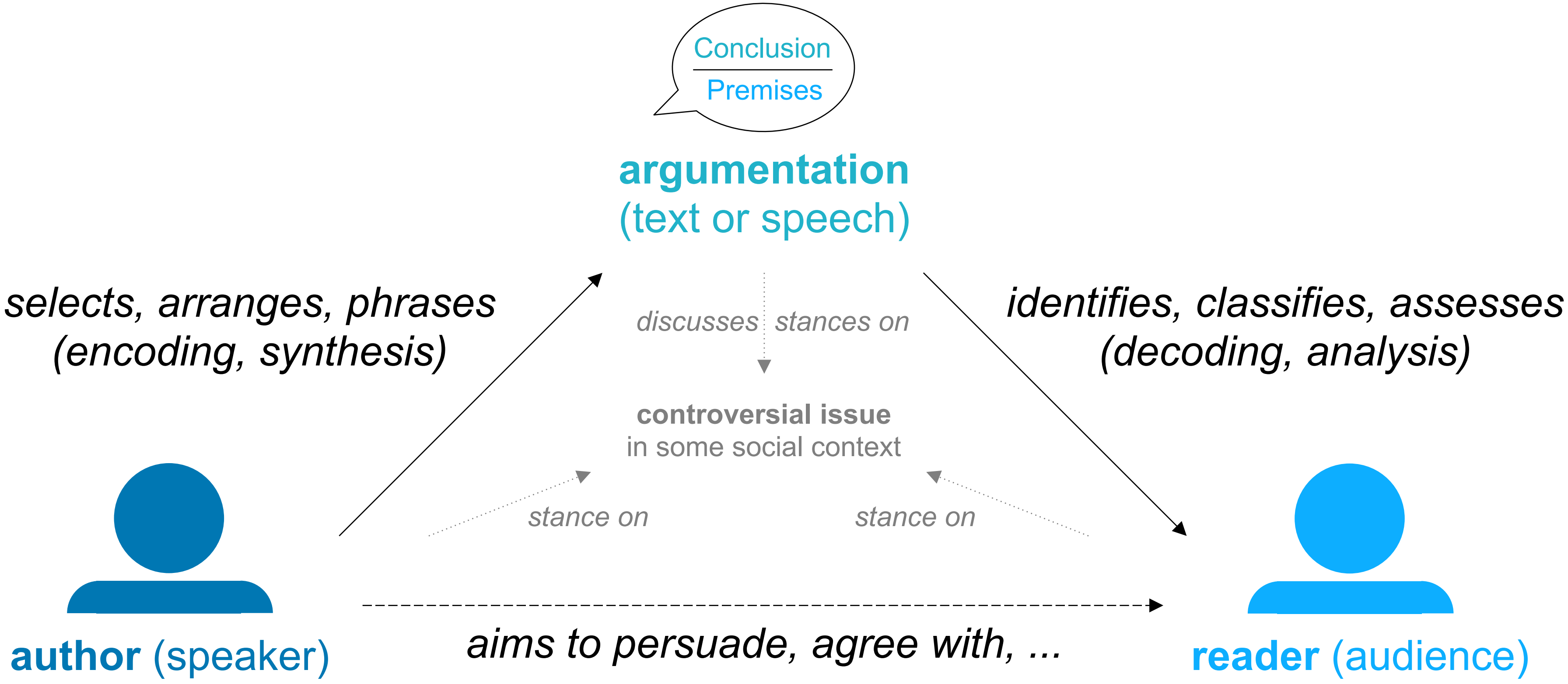
”… in the Mediterranean Sea. Many innocent refugees will die if there are no rescue boats.“

- **Argument generation tasks**
  - Writing of a summary of one or more texts
  - Encoding of knowledge in a new unit
  - Reconstruction of implicit units
  - Composition of units in an argument
  - Creation of a new argumentative text
  - Modification of existing units or arguments

    ... along with variations of these

- **Why argument generation?**
  - Technologies such as Project Debater should be able to form new arguments.
  - Computers may be able to find new argumentative connections.

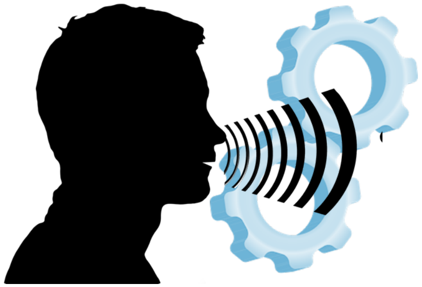
General argumentation setting (recap)



- **Generation vs. mining and assessment**
  - Argument generation refers to the encoding/synthesis side.
  - Still, mining and assessment may be required to decide what to generate.
    e.g., starting from what the opponent argued before

Natural language generation (NLG)

- **Natural language generation (NLG)**
  - Algorithms for the synthesis of natural language (text)
  - The goal is to encode structured or semi-structured information in an unstructured text



https://de.wikipedia.org
https://pixabay.com

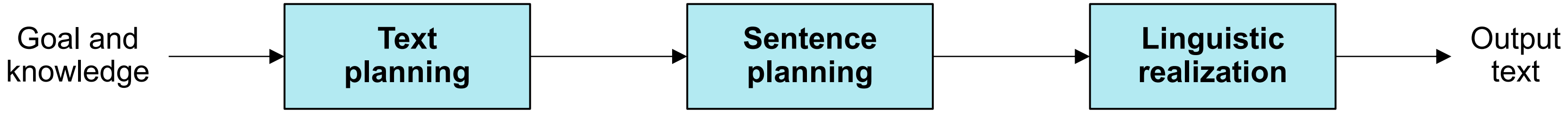
- **Two general types of NLG**
  - Data-to-text. Phrase a new text with data from a knowledge base.
  - Text-to-text. Write an output text in response to a given input text.

- **What makes NLG challenging?**
  - NLG requires to *choose* and *create* a specific text among many potential candidate text.
  - Challenges. Grammaticality, coherence, naturalness, and many more

- **Disclaimer**
  - Only a high-level introduction to selected NLG techniques is given below; more may be needed for working with NLG in general.

NLG process and techniques

- **A full NLG process** based on Reiter and Dale (1997)
  - Input. A goal of what to generate, and knowledge represented in some way
  - Output. A natural language text



- **Main steps**
  - Text planning. Select content, arrange the discourse structure of sentences
  - Sentence planning. Aggregate sentence content, make lexical choices, build referring expressions, ...
  - Linguistic realization. Orthographic, morphological, and syntactic processing

- **NLG techniques detailed below**
  - Summarization, composition, language models, text style transfer, and similar
  - Often, different techniques need to be combined adequately.

Evaluation of NLG

- **How to evaluate NLG?**
  - Goal. Judge quality of generated texts.
  - Problem. There is not *the* correct output.

Ground truth. *”Ban death penalty.“*

Generated text. *”We should ban the death penalty forever.“*

- **Two types of NLG evaluation** (details below)
  - Automatic. Quantify similarity between ground-truth text and generated text based on their words or embeddings.
    Other, partly more task-specific metrics have been proposed, but are not used often (due to comparability).
  - Manual. Assess quality dimensions of generated texts with humans.
- **Main criticisms of automatic evaluation metrics**
  - Uninterpretability. Errors are not distinguishable, not all ”errors” are wrong.
  - Unreliability. Automatic and human assessment often do not correlate.
- **Dilemma of evaluation**
  - Only manual evaluation is seen as reliable, but it costs time and money.
  - Automatic evaluation is needed to observe progress during development.

Evaluation of NLG: Automatic metrics

- **Overview of automatic metrics**
  - BLEU. Precision of *n*-gram overlap with brevity penalty
  - METEOR. F-score of 1-grams with word-order penalty, weighting recall 9x
  - ROUGE. Recall of *n*-gram overlap, either for a specific *n* or averaged
  - BERTScore. F_1-score derived from similarity matching of BERT embeddings

- **BiLingualEvaluation Understudy (BLEU) score**
  - Given all *n*-grams in ground-truth texts D_{gt}, and all generated *n*-grams in D_{gn}
  - Modified *n*-gram precision. Fraction of D_{gn} that matches any *n*-gram in D_{gt}, counting each *n*-gram in D_{gt} once only
  - Brevity penalty. Prevents high scores for short texts to account for recall

$$BLEU = \underbrace{\exp\Big(\sum_{d \in D_{gn}} \frac{1}{n} \cdot \log}_{\text{geometric mean}} \underbrace{\frac{\#ngram\ matches(d)}{\#ngrams(d)}}_{\text{modified precision for generated text } d} \Big) \cdot \underbrace{\exp\Big(\min\{1 - \frac{\#words(D_{gt})}{\#words(D_{gn})}, 0\} \Big)}_{\text{brevity penalty}}$$

  - This value is averaged over all considered *n*.

    Usually, *n*≤2 or *n*≤4 is used, and case sensitivity is ignored. BLEU scores are in [0,1], sometimes multiplied by 100.

Evaluation of NLG: Manual evaluation

- **Manual evaluation**
  - Multiple human annotators assess the quality of a sample of generated texts.
- **Assessment**
  - Absolute scores on a Likert scale (say, 1–5) or relative ranking of candidates
  - The mean or majority judgment of annotators is used for evaluation.
  - As for corpora, inter-annotator agreement can be computed to assess reliability.

    Also, many other principles from lecture part IV apply here.
- **Quality dimensions**
  - What dimensions to be assessed, is to some extent task-specific.
  - Some dimensions are very common according to a literature survey. (van der Lee et al., 2019)

Quality dimension	#
Fluency	13
Naturalness	8
Quality	5
Meaning preservation	5
Relevance	5
Grammaticality	5
Overall quality	4
Readability	4
Clarity	3
Manipulation check	3
Informativeness	3
Correctness	3
… others with count ≤ 2	35

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Argument summarization

- **Argument summarization**
  - The generation of a summary from one or more argumentative texts
  - Input. An argumentative text or a set of texts
  - Output. A summary in terms of a short text, a set of key points, or similar

> *Climate Change is causing the Earth to warm up measurably, and there are already signs of disaster. I argue that this is happening because there are scientific facts to prove it. Out of 918 peer-reviewed scientific papers on this subject, 0% disagreed that climate change is happening, but in newspaper articles, 53% were unsure. This proves that climate change is happening, but scientists are having trouble conveying the information and other data to the people of the world.*

→ *There is no doubt that climate change is causing global warming. In a survey of 918 scientific papers, no one disagreed with this.*

Argument summarization: Example

- **Example: Extractive argument summarization**
  - What are the two most important sentences to understand the argument?

> *The Supreme Court decided that states can't outlaw abortion because Prohibiting abortion is a violation of the 14th Amendment, according to the Court, and the constitution. Outlawing abortion is taking away a human right given to women. In reality, a fetus is just a bunch of cells. It has not fully developed any vital organs like lungs. This means that an abortion is not murder, it is just killing of cells in the wound. If the child has no organs developed that would be vital for the baby to survive outside the wound, than having an abortion is not murder.*

- **Challenges**
  - Argumentative texts may combine multiple claims and reasons.
  - What is most important, may be seen subjectively.
  - Unlike here, a good summary may often require rephrasing.

  ... among other challenges

Background: Summarization in NLG

- **Summary**
  - A short(er) text, derived from one or more long(er) texts, that presents the information important in a given context in a coherent fashion

- **Summarization**
  - The computational generation of a summary of one or more texts

    An extensively-studied NLP task, with many applications
  - Techniques include clustering, graph analyses, neural text generation, …

- **Extractive vs. abstractive summarization**
  - Extractive. Create summary by reusing portions of text (with no/few changes).
  - Abstractive. Reformulate core content by using new words or paraphrases.

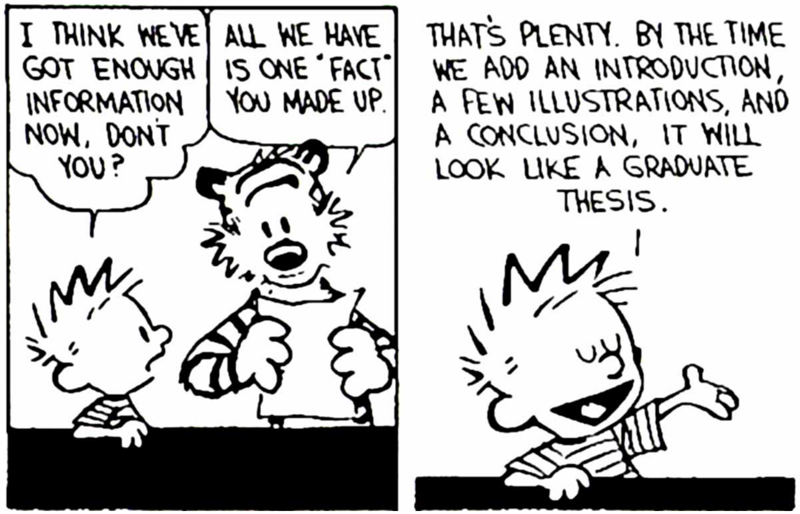
    Both are seen as generation tasks, because the output is a new text.

- **Single vs. multi-document summarization**
  - Single. Summarize the information from a single text.
  - Multi. Summarize the information from several somehow related texts.

    While the conceptual difference seems small, very different techniques are used usually.

Argument summarization: Variations and approaches

- **Variations of argument summarization**
  - Extractive. Identify most important units (or similar) and return them.
  - Abstractive. Reformulate the gist of the arguments in new words or paraphrases.
  - Single vs. multi. Whether the input is one argumentative text, a whole debate, or similar


I THINK WE'VE GOT ENOUGH INFORMATION NOW, DON'T YOU?
ALL WE HAVE IS ONE "FACT" YOU MADE UP.
THAT'S PLENTY. BY THE TIME WE ADD AN INTRODUCTION, A FEW ILLUSTRATIONS, AND A CONCLUSION, IT WILL LOOK LIKE A GRADUATE THESIS.

https://quotesgram.com

- **Selected approaches to argument summarization**
  - Multi-argument keyphrase clustering for online debates (Egan et al., 2016)
  - Abstractive summarization of texts using neural models (Wang and Ling, 2016)
  - Learning-based mapping of arguments to key points (Bar-Haim et al., 2020)
  - Extractive summarization of arguments with graph methods (Alshomary et al., 2020b)
  - Knowledge-augmented generation of informative conclusions (Syed et al., 2021)

Abstractive summarization of texts (Wang and Ling, 2016)

- **Task**
  - Given multiple reasons on an issue, summarize them into one claim.
- **Approach**
  - Neural sequence-to-sequence model that reads reasons and writes a claim
  - First, a subset of the reasons is sampled by scoring their value for a summary.
  - Then, an attention-based LSTM learns long-term dependencies.
- **Data**
  - 676 debates with 2259 claims and 17,359 reasons from idebate.org.
- **Results**
  - BLEU 25.8 (Best extractive baseline 15.1)

    Not better in terms of METEOR and ROUGE

Issue: *This House would detain terror suspects without trial.*

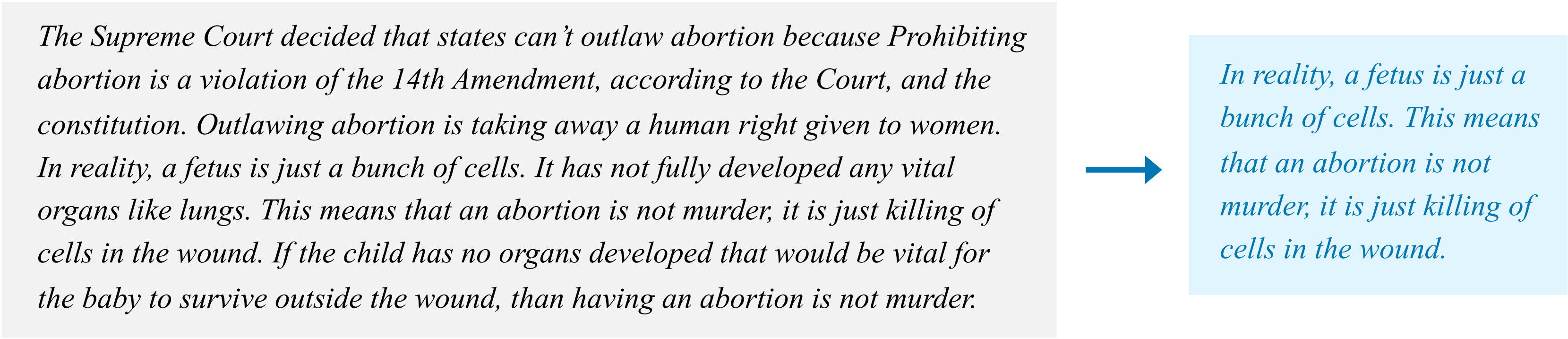
(1) Governments must have powers to protect their citizens against threats to the life of the nation. (2) Everyone would recognise that rules that are applied in peacetime may not be appropriate during wartime.

Human. *Governments must have powers to protect citizens from harm.*

Approach. *Governments have the obligation to protect citizens from harmful substances.*

Extractive summarization of arguments (Alshomary et al., 2020b)

- **Task**
  - Given an argumentative text, generate a two-sentence *snippet* that best represents the gist of the argumentation.



The Supreme Court decided that states can't outlaw abortion because Prohibiting abortion is a violation of the 14th Amendment, according to the Court, and the constitution. Outlawing abortion is taking away a human right given to women. In reality, a fetus is just a bunch of cells. It has not fully developed any vital organs like lungs. This means that an abortion is not murder, it is just killing of cells in the wound. If the child has no organs developed that would be vital for the baby to survive outside the wound, than having an abortion is not murder.

→

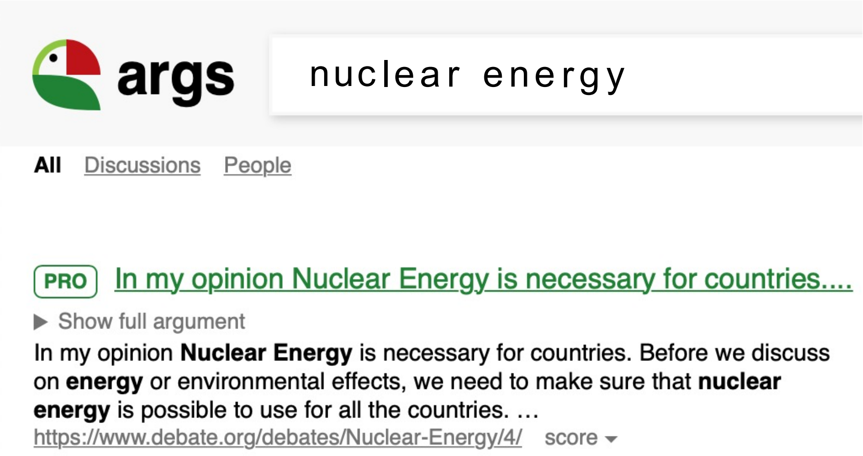
In reality, a fetus is just a bunch of cells. This means that an abortion is not murder, it is just killing of cells in the wound.

- **Research question**
  - How important are the context and argumentativeness of a sentence?

- **Approach in a nutshell**
  - Compute a representativeness score of each sentence from its centrality in its context and its argumentativeness.
  - Return the two sentences with highest score in their original ordering.

Extractive summarization of arguments: Snippets

- **Snippet**
  - A short text that helps to assess the relevance of a search result
  - In general web search, a snippet usually shows a content excerpt containing the query terms.



In my opinion Nuclear Energy is necessary for countries....

In my opinion **Nuclear Energy** is necessary for countries. Before we discuss on **energy** or environmental effects, we need to make sure that **nuclear energy** is possible to use for all the countries. …

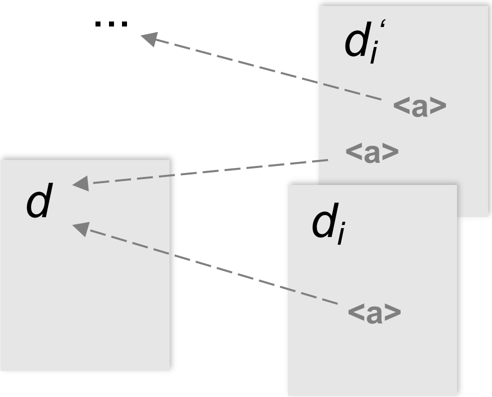
https://www.debate.org/debates/Nuclear-Energy/4/

- **Snippets in argument search**
  - Snippets are key to get an efficient overview of search results.
  - This is of special importance in argument search, where it is often not enough to obtain only one relevant result.
  - Standard snippets may be not enough for arguments. (as in the example above)

- **What is a good argument snippet?**
  - Hypothesis. A short text representing the gist of an argument, in terms of the main claim and main reason supporting the claim.
  - The approach presented here generates *query-independent* snippets.

Extractive summarization of arguments: Approach

- **PageRank** (recap)
  - An unsupervised method to recursively assess the objective importance of a web page
  - Main idea. A page is more important the more other important pages link to it.



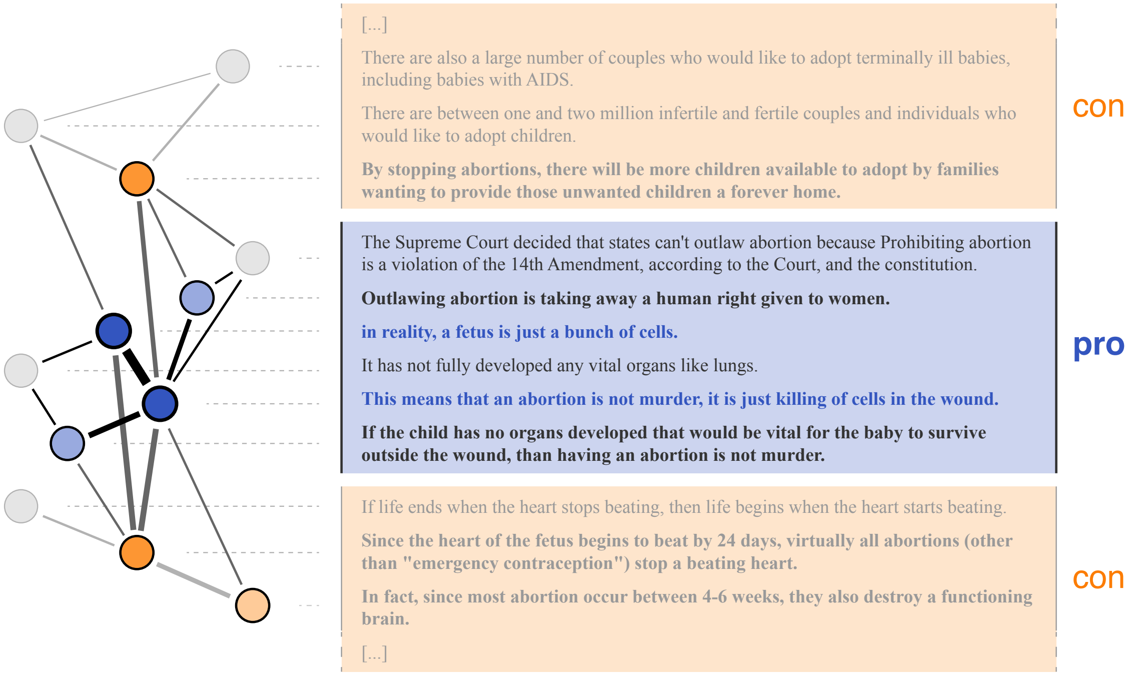
- **LexRank** (Erkan and Radev, 2004)
  - Adaptation of PageRank to assess the *centrality* of a sentence in a text
  - Main idea. A sentence is more important the more similar it is to other important sentences in the same text.

- **LexRank for extractive summarization**
  - Compute LexRank score for all sentences in the context of an argument.
  - Bias the score to sentences that are argumentative.

$$P(s_i) = (1-\alpha) \cdot \sum_{s_j \neq s_i} \underbrace{\boxed{\frac{sim(s_i, s_j)}{\sum_{s_k \neq s_j} sim(s_j, s_k)}}}_{\text{Centrality as "exclusive" sentence similarity}} P(s_j) + \alpha \cdot \underbrace{\boxed{\frac{arg(s_i)}{\sum_{s_k} arg(s_k)}}}_{\text{Bias to argumentative sentences (normalized)}}$$

Extractive summarization of arguments: Realization

- **How to model context?**
  - For debates, the other arguments there serve as suitable context.
  - In other scenarios, arguments could be clustered; each cluster is then one context.



[...]

There are also a large number of couples who would like to adopt terminally ill babies, including babies with AIDS.

There are between one and two million infertile and fertile couples and individuals who would like to adopt children.

By stopping abortions, there will be more children available to adopt by families wanting to provide those unwanted children a forever home.

The Supreme Court decided that states can't outlaw abortion because Prohibiting abortion is a violation of the 14th Amendment, according to the Court, and the constitution.

Outlawing abortion is taking away a human right given to women.

in reality, a fetus is just a bunch of cells.

It has not fully developed any vital organs like lungs.

This means that an abortion is not murder, it is just killing of cells in the wound.

If the child has no organs developed that would be vital for the baby to survive outside the wound, than having an abortion is not murder.

If life ends when the heart stops beating, then life begins when the heart starts beating.

Since the heart of the fetus begins to beat by 24 days, virtually all abortions (other than "emergency contraception") stop a beating heart.

In fact, since most abortion occur between 4-6 weeks, they also destroy a functioning brain.

[...]

- **How to compute similarity and argumentativeness?**
  - Similarity. Cosine similarity between the sentences‘ embeddings

    Simply put, sentence embeddings generalize the idea of word embeddings to sentences.
  - Argumentativeness. Frequency of words from a discourse lexicon

    Argument mining performed worse in experiments, possibly due to heterogeneous input.

- **Notice**
  - These are realization details that could be replaced.

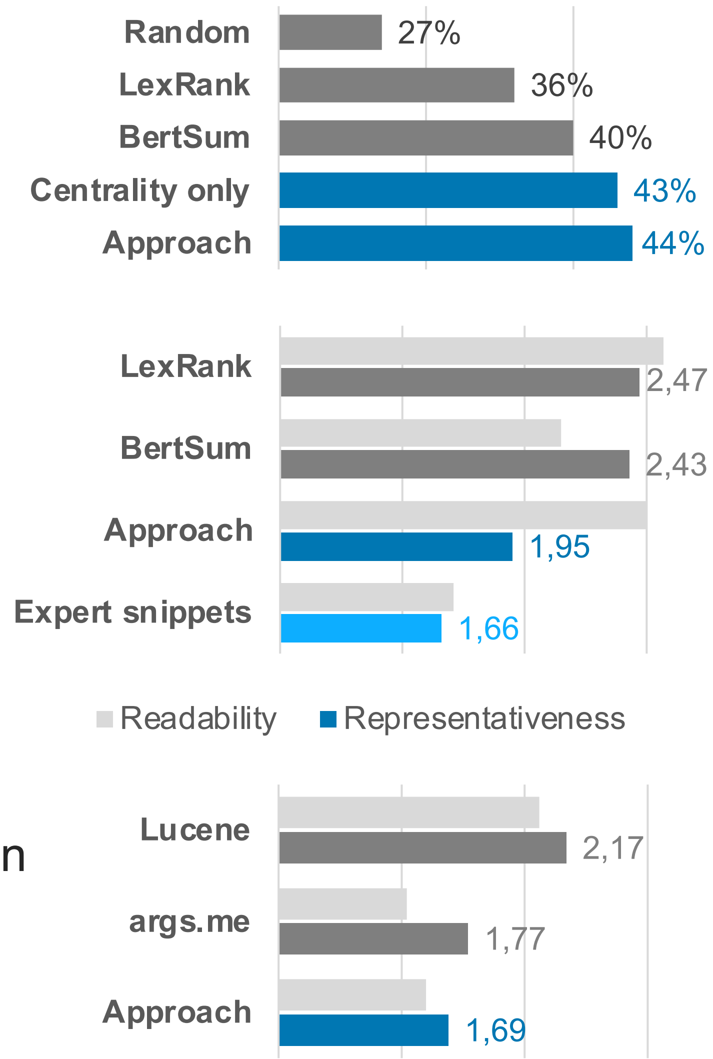
Extractive summarization of arguments: Results

- **Evaluation**
  - Data. Expert snippets for 50 args.me results
  - Automatic. Accuracy of snippet generation
  - Manual. Mean rank of representativeness and readability (from 3 annotators)

- **Extractive summarization baselines**
  - Random. Selecting any 2 sentences
  - LexRank. Simple PageRank for sentences
  - BertSum. Neural extractive summarization
  - Expert snippets. Ground truth

- **Existing snippet generation baselines**
  - Lucene. Query-dependent snippet generation
  - args.me. Using the beginning of arguments

(all snippets cut after 225 characters to mimic application)



Extractive summarization of arguments: Example

- **Argument returned to the query ”climate change“**

Climate Change is causing the Earth to warm up measurably, and there are already signs of disaster. I argue that this is happening because there are scientific facts to prove it. Out of 918 peer-reviewed scientific papers on this subject, 0% disagreed that climate change is happening, but in newspaper articles, 53% were unsure. This proves that climate change is happening, but scientists are having trouble conveying the information and other data to the people of the world.

- **Which snippet best represents the gist of the argument?**

#1. *Climate Change is causing the Earth to warm up measurably, and there are already signs of disaster… I argue that this is happening because there are scientific facts to prove it…*

args.me

#2. *Out of 918 peer-reviewed scientific papers on this subject, 0% disagreed that climate change is happening, but in newspaper articles, 53% were unsure… This proves that climate change is happening, …*

approach

#3. *Climate Change is causing the Earth to warm up measurably, and there are already signs of disaster … reviewed scientific papers on this subject, 0% disagreed that climate …*

Lucene

Argument summarization: Discussion

- **How complex is argument summarization?**
  - Summarization is a hard task in general, since a good summary may require deep text understanding.
  - Abstractive summarization is notably more complex, but more human-like.
  - As usual, the more narrow the domain of texts, the better it may work.
- **What is a good argument summary?**
  - An argument summary should represent the main reasoning well.
  - How much subjectiveness should be kept, depends on the application.
  - Not much research exists so far on how to best summarize argumentation.

    The work of Alshomary et al. (2020b) is the first to explicitly raise this question.
- **Why argument summarization?**
  - Not only in argument search, short argument summaries are needed.
  - Getting an overview of different or longer arguments is important in many applications of computational argumentation.

    Rationale behind: We cannot always consume all information out there.

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Argument composition and creation

- **Argument composition**
  - The synthesis of argumentative units, arguments, and full argumentative texts from existing bulding blocks
  - Input. An issue, possibly a stance, and possibly knowledge given in some way
  - Output. A text arguing on the given issue

Pro
rescue boats →

> *"If you wanna hear my view, I think that the EU should allow rescue boats in the Mediterranean Sea. Many innocent refugees will die if there are no such boats. While having such boats may make even more people die trying, nothing justifies to endanger the life of innocent people. Got it?"*

- **Argument creation**
  - The generation of new argument units, arguments, or full argumentative texts
  - Input/Output. As above

Con
rescue boats →

> *"Having **rescue boats** makes even more **people die** trying."*

Argument composition and creation: Examples

- **Example: Reason creation**
  - Given the following claim, phrase a meaningful reason for it.

A university degree is important for your career.

▼

Employers look at what degree you have first.

TRUMP'S ASTONISHING CLAIM!
OBAMA WIRETAPPED MY PHONES!!
WATCH ME PULL OUT THE EVIDENCE!
©DAVEGRANLUND.COM

- **Challenges**
  - Knowledge bases might not contain suitable concepts for everything.
  - Connections between different concepts build on world knowledge.
  - Content, reasoning, and stance all need to be encoded properly.
  - Linguistic adaptations of grammar may be necessary.

Argument composition and creation: Approaches

- **Variations of argument composition and creation**
  - Template filling. Fill slots with concepts from knowledge base or other texts.
  - Language modeling. Generate free text based on trigger concepts.
  - Controlled generation. Generate free text that fulfills specified constraints.

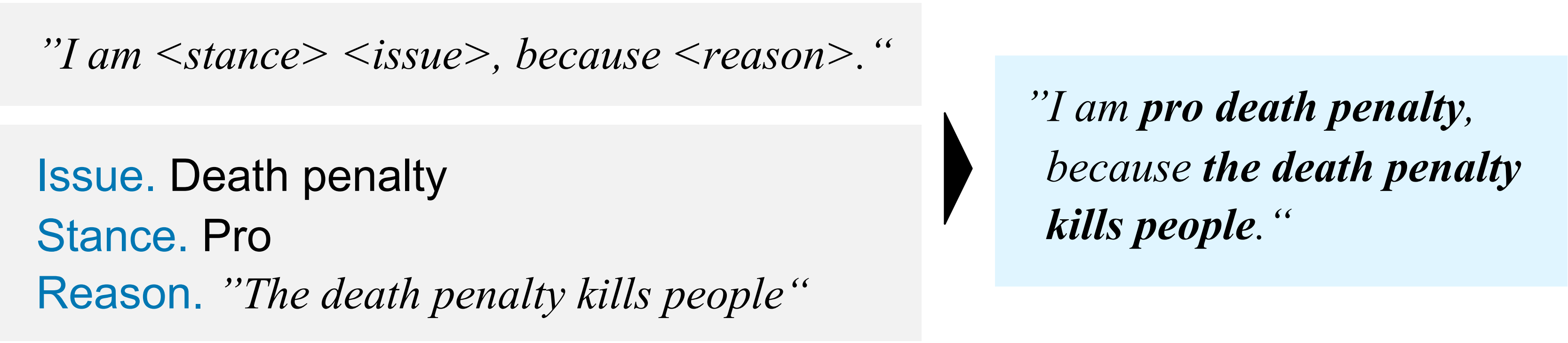
- **Selected approaches to argument composition**
  - Discourse planning for argumentative texts (Zukerman et al., 2000)
  - Knowledge-based scoring for argument composition (Sato et al., 2015)
  - Predicate recycling for composing new claims (Bilu and Slonim, 2016; 2019)
  - Language modeling for rhetorical argument composition (El Baff et al., 2019)

- **Selected approaches to argument creation**
  - Neural target inference in conclusion generation (Alshomary et al., 2020a)
  - Neural knowledge encoding in argument generation (Al-Khatib et al., 2021)
  - Transformer-based generation of conclusions for assessment (Gurcke et al., 2021)
  - Conditioned neural generation of claims with beliefs (Alshomary et al., 2021a)

Background: NLG via composition

- **What is meant by composition?**
  - The generation of a text by selecting and arranging existing text fragments
  - Phrasing is adjusted only to account for grammaticality and coherence.
    Examples: Change from singular to plural, addition of discourse markers, capitalization

- **How to compose?**
  - Simple rule-based techniques start from sentence and discourse templates whose slots are filled with information.



”I am <stance> <issue>, because <reason>.“

Issue. Death penalty
Stance. Pro
Reason. *”The death penalty kills people“*

*”I am **pro death penalty**, because **the death penalty kills people**.“*

  - Composition can also be learned and encoded in statistical models, e.g., in language models.

Predicate recycling for claim synthesis (Bilu and Slonim, 2016)

- **Task**
  - Given a target, generate a claim on the target.

great anarchy

a global language

nuclear weapons

democratization

- **Data**
  - For 67 iDebate topics, 28 claims derived from Wikipedia.
  - Each claim labeled as good or bad 5 times (majority label used)

    “Good” means coherent and relevant to the topic.

- **Approach**
  - Identification. Parse existing claims to extract stance-bearing predicates.
  - Composition. Sort predicates by similarity to target, then construct candidate target-predicate pairs.

    Linguistic adaptations via an off-the-shelf library
  - Selection. Score each candidate using regression.

    Features: Length, *n*-gram matches with Wikipedia, ...

cause lung cancer

contribute to stability

is a source of conflict

lead to great exhaustion

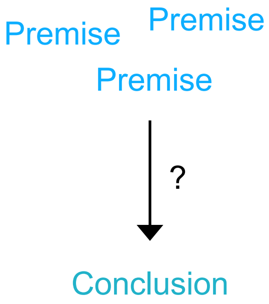
Democratization contributes to stability.

Nuclear weapons cause lung cancer.

- **Results**
  - Mean precision 0.93@1, 0.75@10

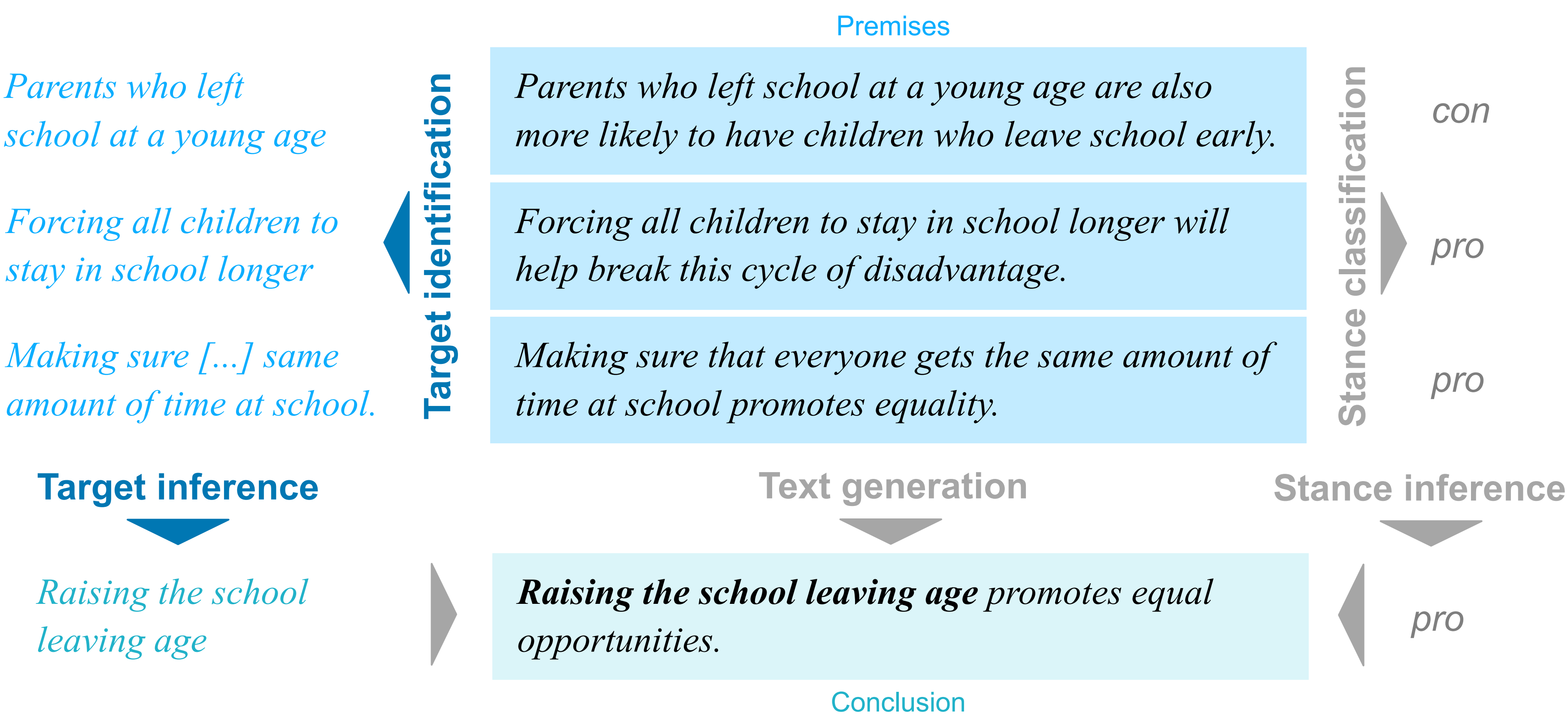
Target inference in conclusion generation (Alshomary et al., 2020a)

- **Task**
  - Given the premises of an argument, infer (the target of) its conclusion.
    Only the *target* inference tackled in this work
  - Motivation. Humans often leave parts of arguments implicit.
    Particularly, conclusions often left out (Habernal and Gurevych, 2015)



- **Hypothesis**
  - The conclusion target is related to the targets of the premises.
- **Data**
  - iDebate. 2259 arguments (Wang and Ling, 2016)
  - Essays-c. 2020 premise-conclusion arguments (Stab, 2017)
  - Essays-t. 402 conclusion-thesis arguments (Stab, 2017)
    Each split into training, validation, and test set
- **Two complementary approaches**
  - Either, rank identified premise targets by their representativeness.
  - Or, match generated target embedding with target knowledge base.

Target inference in conclusion generation: Overall idea



Premises

Parents who left school at a young age are also more likely to have children who leave school early.

Forcing all children to stay in school longer will help break this cycle of disadvantage.

Making sure that everyone gets the same amount of time at school promotes equality.

Target identification

Parents who left school at a young age

Forcing all children to stay in school longer

Making sure [...] same amount of time at school.

Stance classification

con

pro

pro

Target inference

Raising the school leaving age

Text generation

***Raising the school leaving age** promotes equal opportunities.*

Conclusion

Stance inference

pro

- **Target identification**
  - State-of-the-art tagger trained on existing data (Bar-Haim et al., 2017; Akbik et al., 2018)

Forcing	*all*	*children*	*to*	*stay*	*in*	*school*	*longer*	*will*	*help*	*break*	*this*	*cycle*	*of*	*disadvantage*	*.*
B	I	I	I	I	I	I	I	O	O	O	O	O	O	O	O

Target inference in conclusion generation: Ranking

- **Inference hypothesis H_1**
  - One of the premise targets represents an adequate conclusion target

- **Approach a_1: Premise target ranking**
  - Model. Prediction of a representativeness score for each candidate target
    Trained on Jaccard similarity of ground-truth premise and conclusion targets, following Wang and Ling (2016)
  - Features. Length, position, sentiment, and similarity to other candidates
  - Inference. Pick most representative premise target

Parents who left school at a young age 0.3

Forcing all children to stay in school longer 0.7 ~ *Raising the school leaving age*

Making sure [...] same amount of time at school. 0.2

- **Implication**
  - A target that is not given in the premises can never be predicted.

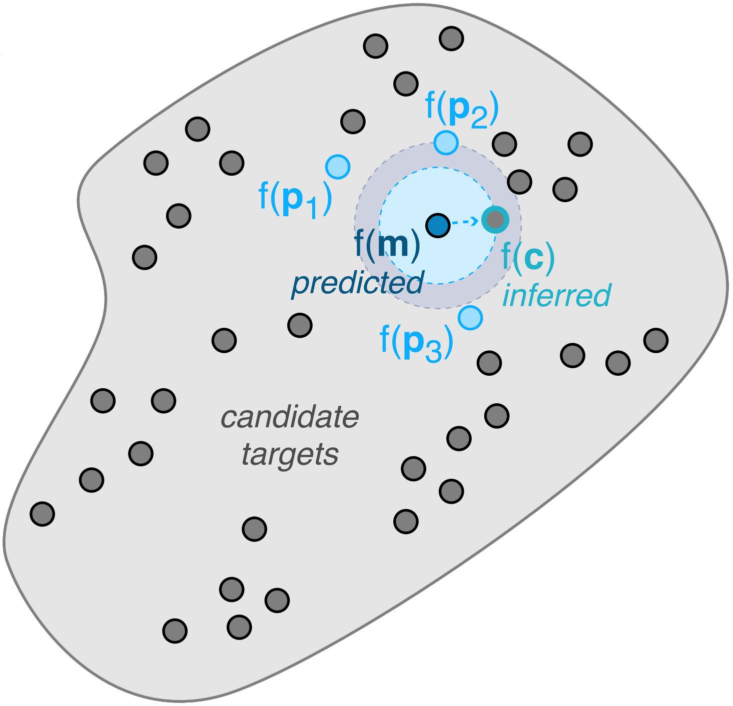
Target inference in conclusion generation: Learning

- **Inference hypothesis H_2**
  - The premise targets are semantically related to adequate conclusion targets

- **Approach a_2: Embedding learning**
  - Learn to map premise target embeddings to conclusion target embedding.

    Details on next slides
  - Embed candidate targets from some knowledge base.
  - Pick candidate target whose embedding is closest to premise targets.

Learned target embedding space

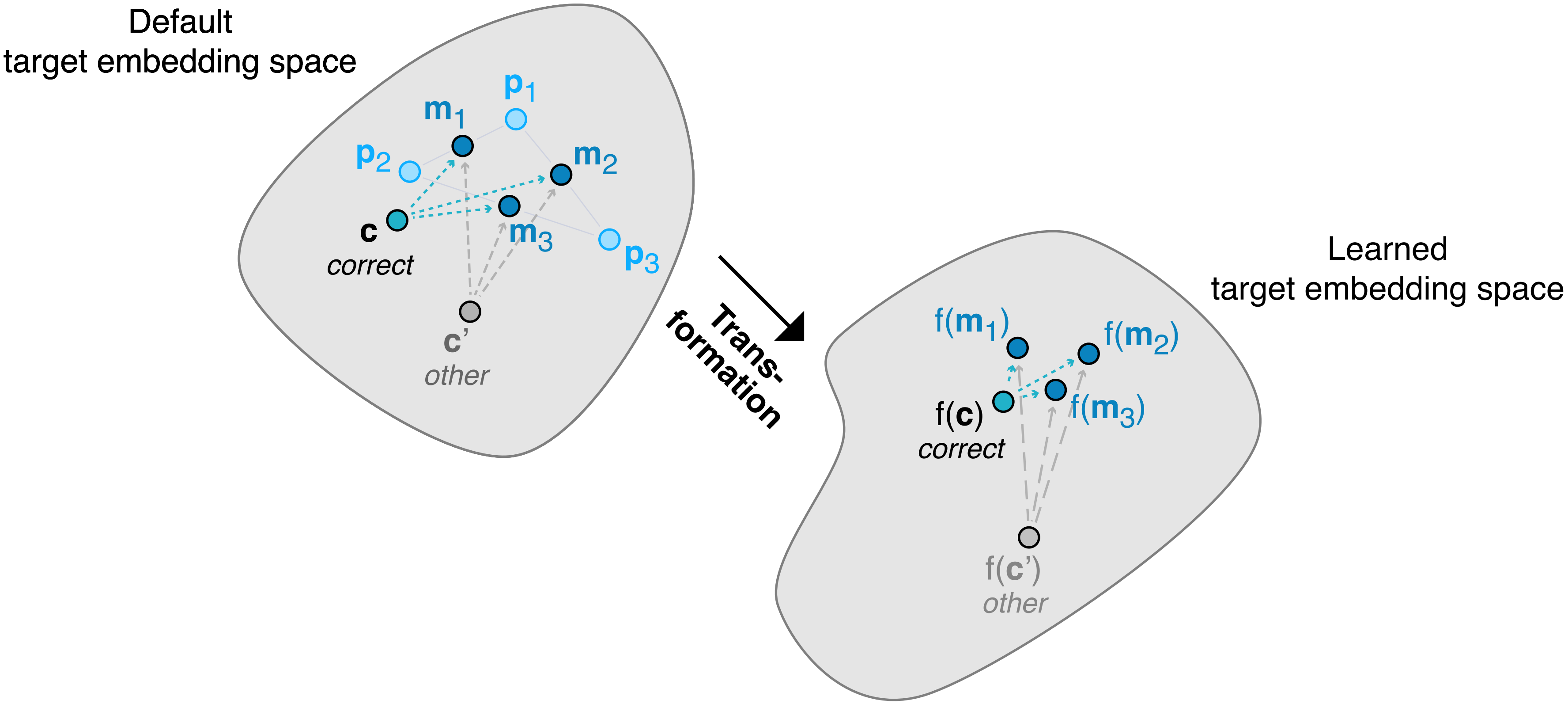


- **Implications**
  - Guarantees to obtain a meaningful target
  - Depends on quality of target knowledge base

    In the experiments, targets identified in training arguments used

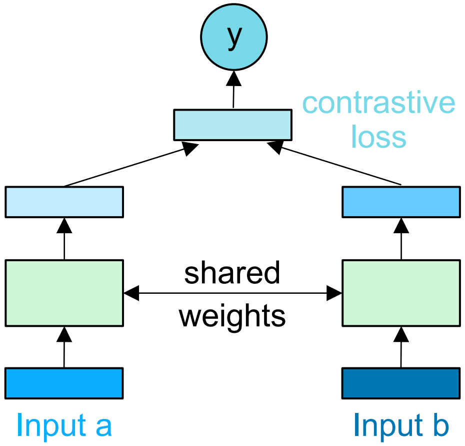
Target inference in conclusion generation: Embeddings

- **Contrastive learning of target embeddings**
  - Compute means $\mathbf{m}_1, \ldots, \mathbf{m}_l$ of premise target embeddings $\mathbf{p}_1, \ldots, \mathbf{p}_k$.
  - Learn model *f* that makes $\mathbf{m}_i$ more similar to correct conclusion target *f(***c***)* and less similar to other targets *f(***c***‘).*

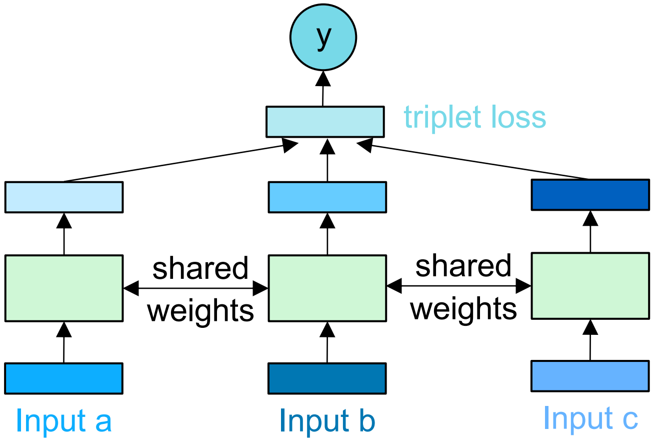


Background: Siamese and triplet neural networks

- **Siamese neural network (SNN)**
  - Two networks sharing the same weights to transform two inputs *a* and *b* into two outputs
  - The difference of outputs is quantified as a distance *d*.
  - Contrastive loss function. The learning objective is to minimize *d* between similar inputs and to maximize it for dissimilar inputs.

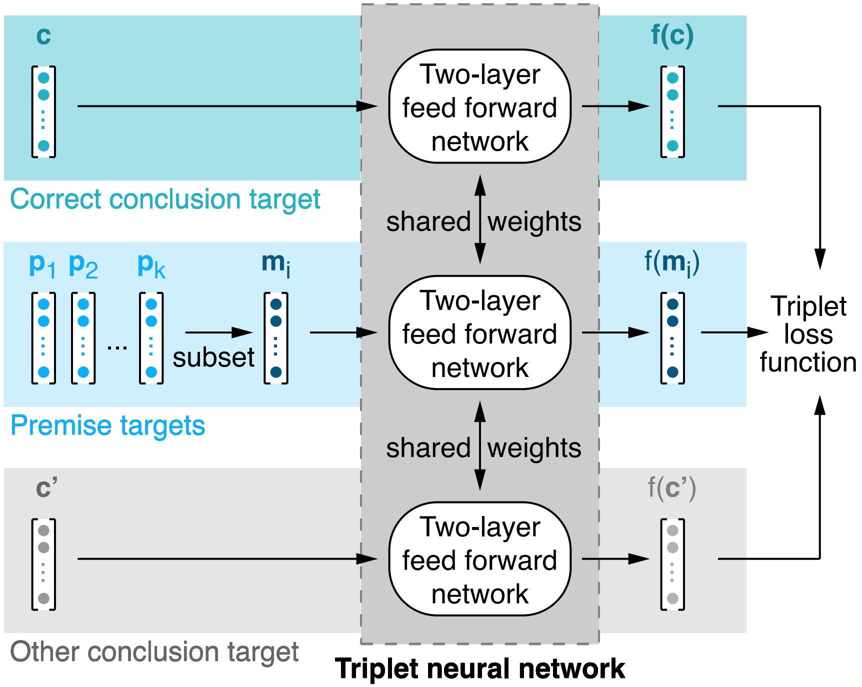


- **Triplet neural network (TNN)**
  - A TNN follows a similar idea to an SNN for three inputs *a, b, c*.
  - One input (say, *b*) is used to define distance.
  - Triplet loss function. The learning objective is to minimize the distance *d* between *a* and *b* and to maximize it for *b* and *c.*



Target inference in conclusion generation: Optimization

- **How to learn the mapping**
  - Train triplet neural network on targets from complete arguments



  - Optimize loss function based on distance to correct and to other target:

$$\mathcal{L} = \max\left\{\underbrace{d(f(\mathbf{m}_i), f(\mathbf{c}))}_{\text{Distance to correct target}} - \underbrace{d(f(\mathbf{m}_i), f(\mathbf{c}'))}_{\text{to wrong target}} + \underbrace{d_{max}}_{\text{considered maximum (hyperparamater)}},\ 0\right\}$$

Target inference in conclusion generation: Results

- **Baselines and hybrid approach**
  - Seq2Seq*. Summarize premises, tuned to their targets. (Wang and Ling, 2016)
  - Premise target (random). Pick one premise target randomly.
  - Embedding (mean). Pick candidate that most resembles premise targets.
  - Hybrid approach. a_2 if inferred target overlaps with any premise, otherwise a_1

- **Evaluation**
  - Automatic. BLEU score for 1- and 2-grams on each dataset
  - Manual. Percentage of fully/somewhat adequate targets (only on iDebate)

Approach	iDebate	Essays-c	Essays-t	Fully	Somewhat	Not
Seq2Seq*	4.4	–	–	5%	18%	**76%**
Premise target (random)	3.9	2.2	8.8	–	–	–
Embedding (mean)	7.2	**8.3**	15.3	–	–	–
Premise target ranking	9.7	4.1	17.3	**56%**	33%	11%
Embedding learning	9.2	**8.3**	**27.9**	50%	28%	22%
Hybrid approach	**10.0**	8.2	**27.9**	55%	**34%**	11%

Target inference in conclusion generation: Examples

- **Input: A set of premise targets**

Example 1	Example 2	Example 3
how to use the mobile phone	*Relocating to the best universities*	*Saving the use of that kinds of languages*
Phones	*Improving the pool of students*	*in this case*
Having a mobile phone	*Online courses*	*to be respected and preserved*
the internet phones	*Stanford University's online course on Artificial Intelligence*	*language*

- **Output: One conclusion target**

	Example 1	Example 2	Example 3
ground truth	*Mobile phones*	*Online courses*	*the government*
ranking	*Phones*	*Online courses*	*language*
inference	*Mobile phones*	*distance-learning*	*language acquisition*

Generation of conclusions for assessment (Gurcke et al., 2021)

- **Assessment task**
  - (Local) Sufficiency. An argument‘s premises make it rationally worthy to draw the conclusion. (Johnson and Blair, 2006)
  - Given an argument, decide whether it is sufficient or not.

Conclusion

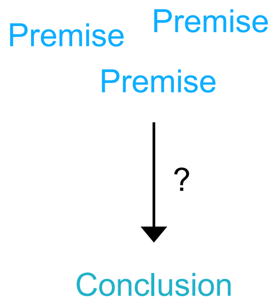
*Last, **we should develop at least one personal hobby, not to show off, but express our emotion when we feel depressed or pressured**. Playing musical instrument is a good way, I can play guitar. When I meet difficulties in studies, I take my guitar and play the song Green Sleeves. It makes me feel better and gives me confidence.*

Premises

→ Insufficient

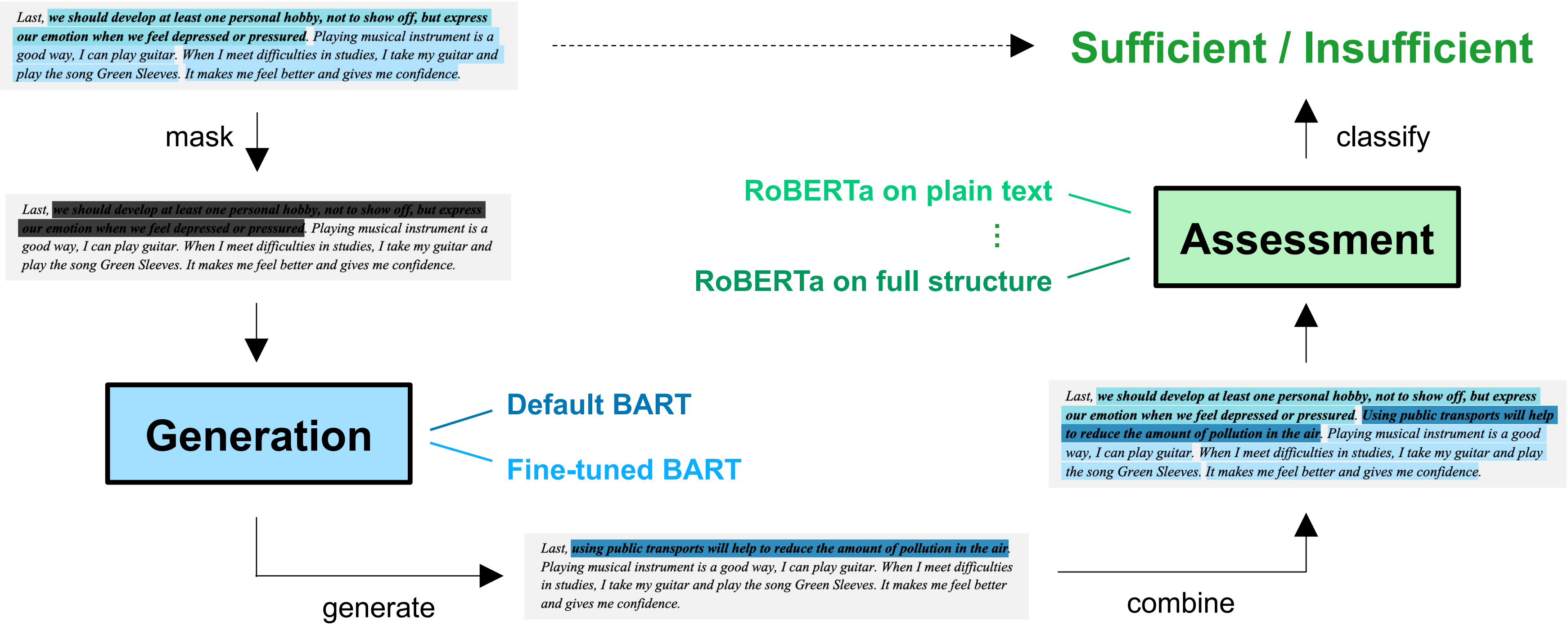
- **Research question**
  - How is local sufficiency reflected in language?

- **Generation task**
  - Hypothesis. Only for sufficient arguments, the conclusion can be *inferred* from their premises.
  - Given an argument‘s premises, generate the conclusion.



Generation of conclusions for assessment: Approach

- **Approach in a nutshell**
  - Generation. Infer a(nother) conclusion from the argument's premises.
  - Assessment. Classify local sufficiency based on the full argument and the inferred conclusion



Last, ***we should develop at least one personal hobby, not to show off, but express our emotion when we feel depressed or pressured***. *Playing musical instrument is a good way, I can play guitar. When I meet difficulties in studies, I take my guitar and play the song Green Sleeves. It makes me feel better and gives me confidence.*

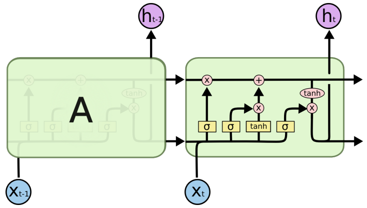
*Last, **we should develop at least one personal hobby, not to show off, but express our emotion when we feel depressed or pressured**. Playing musical instrument is a good way, I can play guitar. When I meet difficulties in studies, I take my guitar and play the song Green Sleeves. It makes me feel better and gives me confidence.*

*Last, **using public transports will help to reduce the amount of pollution in the air**. Playing musical instrument is a good way, I can play guitar. When I meet difficulties in studies, I take my guitar and play the song Green Sleeves. It makes me feel better and gives me confidence.*

*Last, **we should develop at least one personal hobby, not to show off, but express our emotion when we feel depressed or pressured**. **Using public transports will help to reduce the amount of pollution in the air**. Playing musical instrument is a good way, I can play guitar. When I meet difficulties in studies, I take my guitar and play the song Green Sleeves. It makes me feel better and gives me confidence.*

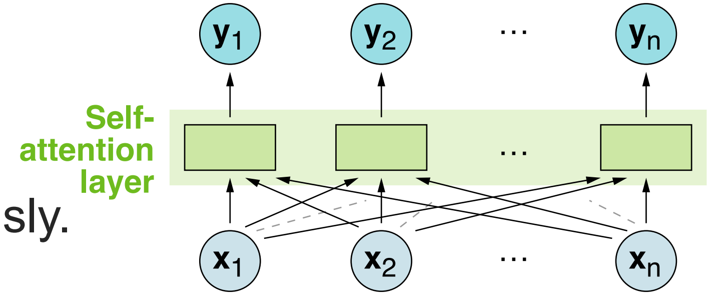
Background: Transformer neural networks

- **LSTM: Recap and problem**
  - RNN with memory to model long-term dependencies
  - Training is slow due to sequential input processing.
  - Long-term memory is still limited by hidden state size.

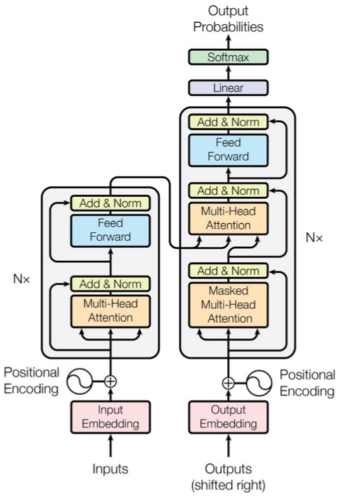


https://colah.github.io

- **Self-attention as a solution?**
  - Model interdependencies between inputs.
  - Different inputs can be modeled simultaneously.



- **Transformer** (Vaswani et al., 2017)
  - A network architecture for sequence-to-sequence generation
    Can be seen as the current state of the art technique in NLP
  - Idea: Make inputs independent while modeling their context.
  - Transformers are based entirely on self-attention.
    More on next slide
  - Faster training due to parallel processing of sequential input
  - Modeling of long-term dependencies largely solved

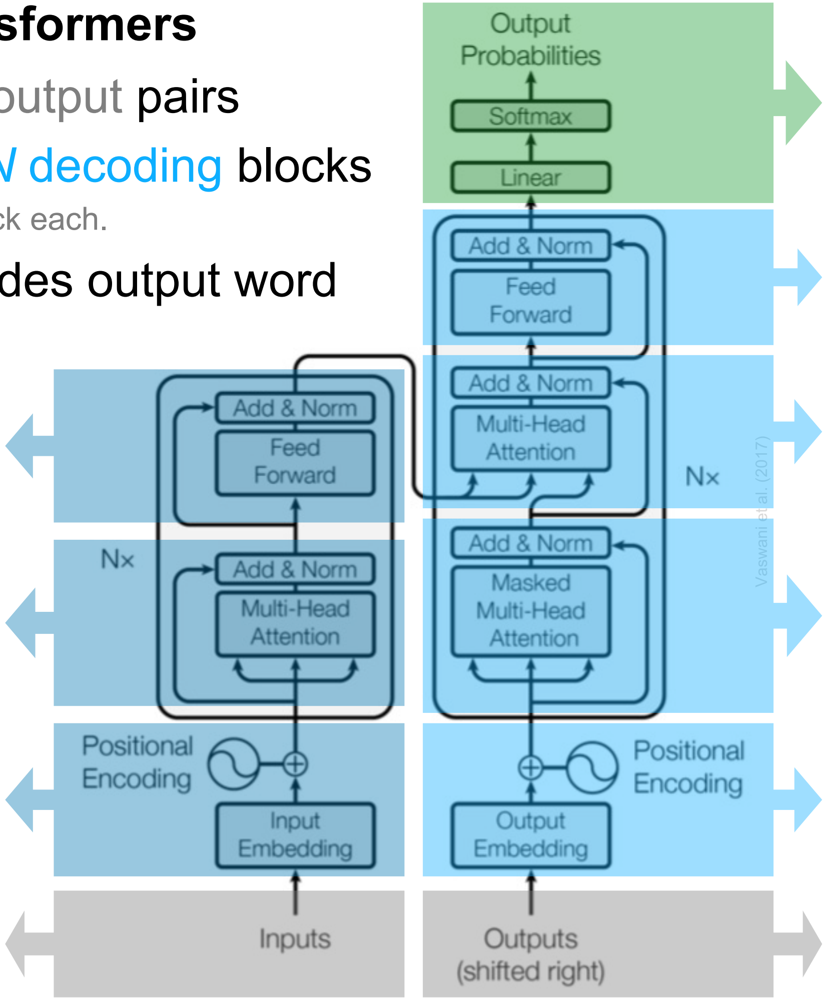


Vaswani et al. (2017)

Background: Encoding and decoding of transformers

- **Architecture of transformers**
  - Trained on input/output pairs
  - *N* encoding and *N* decoding blocks

    Illustration shows one block each.
  - Output head decides output word



Vaswani et al. (2017)

Transform vector into accepted input length

Compute weighted average of multiple self-attention vectors

Add positional information to word embedding

Sequence of input tokens (separately embedded)

Map to probabilities of all possible output words (separately for each word)

Transform vector into accepted input length

Model relations between input and output words

Compute weighted average of multiple self-attention vectors, only based on previous words

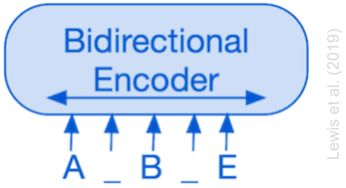
Add positional information to word embedding

Sequence of output tokens (separately embedded)

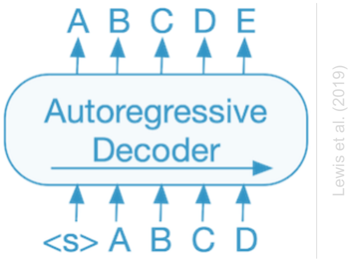
Death penalty kills innocent people.   `<start>` Death penalty should be banned.

Background: Three common transformer variations

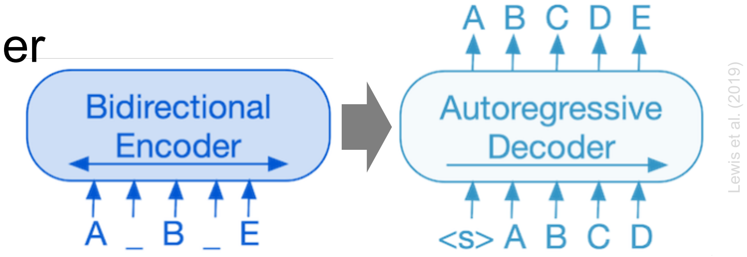
- **Bidirectional transformer (encoder-only)**
  - Models inputs based on both previous and following inputs
  - Usually for classification and regression, via added heads
  - Examples. BERT and RoBERTA
    (Devlin et al., 2019; Liu et al., 2019)



- **Autoregressive transformer (decoder-only)**
  - Models inputs based on previous inputs only
  - Usually for generation, via probability prediction (see above)
  - Examples. GPT-x and Alpaca
    (Radford et al., 2018; Taori et al., 2023)



- **Full transformer (encoder-decoder)**
  - Bidirectional encoder, autoregressive decoder
  - Usually for controlled generation tasks
  - Examples. BART and T5
    (Lewis et al., 2019; Raffel et al., 2020)



Generation of conclusions for assessment: Evaluation

- **Experimental setup**
  - Data. 100 arguments (50% sufficient) from student essays (Stab and Gurevych, 2017)
  - Approaches. Ground truth, default BART, fine-tuned BART
  - Experiments. 5 humans scored 3 relatedness dimensions, scale 1–5

- **Relatedness dimensions**
  - Novelty. How different is the conclusion from the premises?
  - Likeliness. How likely is it to infer the conclusion from the premises?
  - Sufficiency. Are the premises sufficient to draw the conclusion?

- **Manual evaluation results** (mean scores, higher is better)

Approach	Novelty	Likeliness	Sufficiency
Default BART	3.34	2.76	2.87
Fine-tuned BART	3.47	2.96	2.87
Ground truth	**3.79**	**2.98**	**2.92**

Generation of conclusions for assessment: Examples

- **Insufficient argument**

Last, ~~we should develop at least one personal hobby, not to show off, but express our emotion when we feel depressed or pressured~~. Playing musical instrument is a good way, I can play guitar. When I meet difficulties in studies, I take my guitar and play the song Green Sleeves. It makes me feel better and gives me confidence.

but not least, I love music

Default BART

playing musical instrument is very important to me

Fine-tuned BART

- **Sufficient argument**

Second, ~~public transportation helps to solve the air pollution problems~~. Averagely, public transports use much less gasoline to carry people than private cars. It means that by using public transports, less gas exhaust is pumped to the air and people will no longer have to bear the stuffy situation on the roads, which is always full of fumes.

public transport is more efficient than private cars

using public transports will help to reduce the amount of pollution in the air

Generation of conclusions for assessment: Sufficiency

- **Experimental setup** (Stab and Gurevych, 2017)
  - Data. 1029 arguments (66% sufficient) from 402 student essays
  - Experiments. 5-fold cross-validation, 20 repetitions
  - Approaches. CNN baseline, RoBERTa on various *input configurations*

- **Input configurations**
  - Plain text compared to varying subsets of annotated argument structure

- **Results** (higher is better)

Approach	Input	Macro F_1 ↑
RoBERTa (our approach)	Full plain text w/o structure	0.876
	Premises only	0.875
	Premises + generated conclusion	0.878
	Premises + both conclusions	**0.885**
CNN (Stab and Gurevych, 2017)	Full plain text w/o structure	0.831

Argument composition and creation: Discussion

- **Effective argument composition**
  - A grammatically correct text can be generated easily based on templates.
  - The challenge lies in the generation of coherent, relevant, and meaningful text in a given context.
  - In practice, a common strategy is to retrieve and adjust content

- **Effective argument creation**
  - Transformer-based generation has made argument creation well-feasible.
  - The challenge lies in making the arguments fulfill desired properties, such as factuality and audience adjustment.
  - Hybrid composition/creation approaches may allow for more control.

- **Why creation and composition?**
  - Increase of the capabilities of debating technologies, such as Project Debater
  - Support in argumentative writing through auto-completion or similar
  - Potential creation of really new, not yet known arguments?

Outline: Argument rewriting and countering

I. Introduction to computational argumentation

II. Basics of natural language processing

III. Basics of argumentation

IV. Argument mining

V. Argument assessment

VI. Argument generation

- a) Introduction
- b) Argument summarization
- c) Argument composition and creation
- **d) Argument rewriting and countering**
- e) Conclusion

VII. Applications of computational argumentation

VIII. Conclusion

Argument rewriting and countering

- **Argument rewriting**
  - The modification of a unit, argument, or full argumentative text to fulfill some specified goal
  - Input. The text to be rewritten, possibly with a specified goal
  - Output. The rewritten text

AGI are susceptable. → *AGI is susceptible to being hacked.*

- **Argument countering**
  - The generation of a counterargument (or unit) to a given argument (or unit)
  - Input. The argument to be countered
  - Output. An argument opposing to the input argument

The EU should allow rescue boats in the Mediterranean Sea. Many innocent refugees will die if there are no rescue boats. → *Having rescue boats also may have negative effects. Even more people may die trying, believing that they may be rescued.*

Argument rewriting and countering: Examples

- **Examples: Rewriting and countering**
  - Given the following claim, rewrite it to make it more clear.

The death penalty may kill the innocent. ▶ *As long as justice remains fallible, there is a risk that innocent people are killed.*

  - Given the following claim pro death penalty, change it to con death penalty.

The deterrent effect of the death penalty justifies its risks. ▶ *The death penalty's deterrent effect does not justify its risks.*

- **Challenges**
  - Most challenges of argument creation also show up here.
  - The main differences lies in the dependence on the given input.
  - Information added during rewriting/countering should fit and be “truthful”.
  - Not always, paired training data is available for learning.

Argument rewriting and countering: Approaches

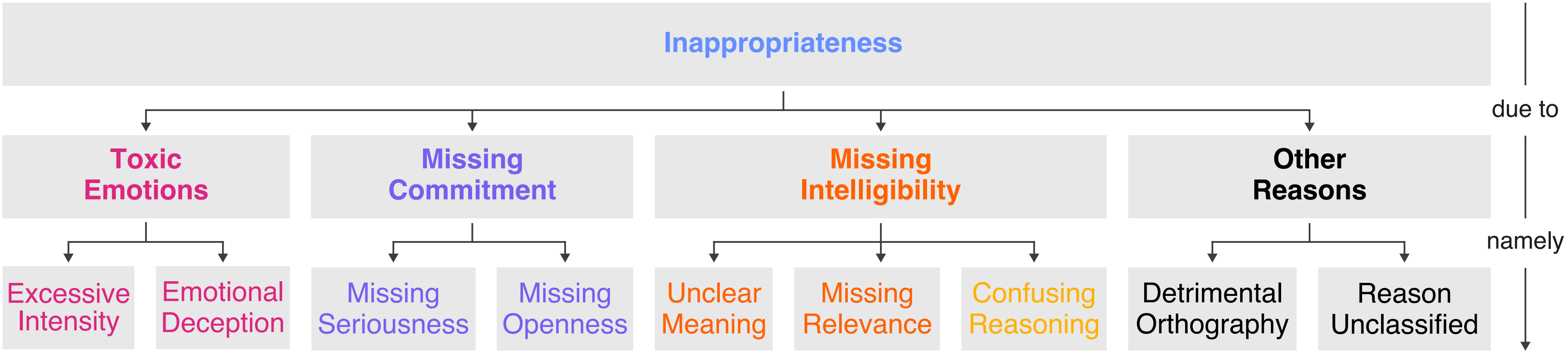
- **Variations of argument rewriting and countering**
  - Sequence-to-sequence. Given a text, rewrite it into another text.
  - Retrieve-delete-rephrase. Find, compose, and possibly adjust relevant units.
  - Conditioned language modeling. Generate free text matching certain criteria.

- **Selected approaches to argument rewriting**
  - Transformer-based low-level neutralization of arguments (Chakrabarty et al., 2021)
  - Neural rewriting and ranking for claim optimization (Skitalinskaya et al., 2023)
  - Reinforcement learning for rewriting inappropriate arguments (Ziegenbein et al., 2024)

- **Selected approaches to argument countering**
  - Retrieval and neural generation of counters (Hua and Wang, 2018; Hua et al., 2019)
  - Neural style transfer for bias modification (Chen et al., 2018)
  - Sequence-to-sequence generation of opposing claims (Hidey and McKeown, 2019)
  - Neural generation of aspect-based counterarguments (Schiller et al., 2020)
  - Conclusion/Counter generation via multitask learning (Alshomary and Wachsmuth, 2023)

Reinforcement-learned argument rewriting (Ziegenbein et al., 2024)

- **Appropriateness of arguments**
  - The language of argument support the creation of credibility and emotions, and it is proportional to the issue (Wachsmuth et al., 2017)
  - Various issues may make an argument inappropriate: (Ziegenbein et al., 2023)

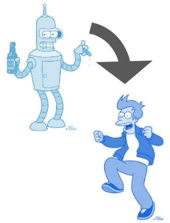


- **Research question**
  - How to make arguments appropriate while preserving their meaning?
- **Hypothesis**
  - The rewriting behavior of LLMs can be aligned based on classifier output, even on non-parallel data.

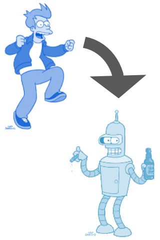
PARENTAL ADVISORY EXPLICIT CONTENT

Background: Alignt of LLMs using PPO

- **Alignment of LLMs**
  - Adjust behavior based on (possibly delayed) human or machine feedback.
  - Often based on reinforcement learning, e.g., using *proximal policy optimization*
  - The goal is to learn a policy that optimizes some cumulative future reward.



Feedback. Answers of LLM assessed



Optimization. LLM adjusts to feedback

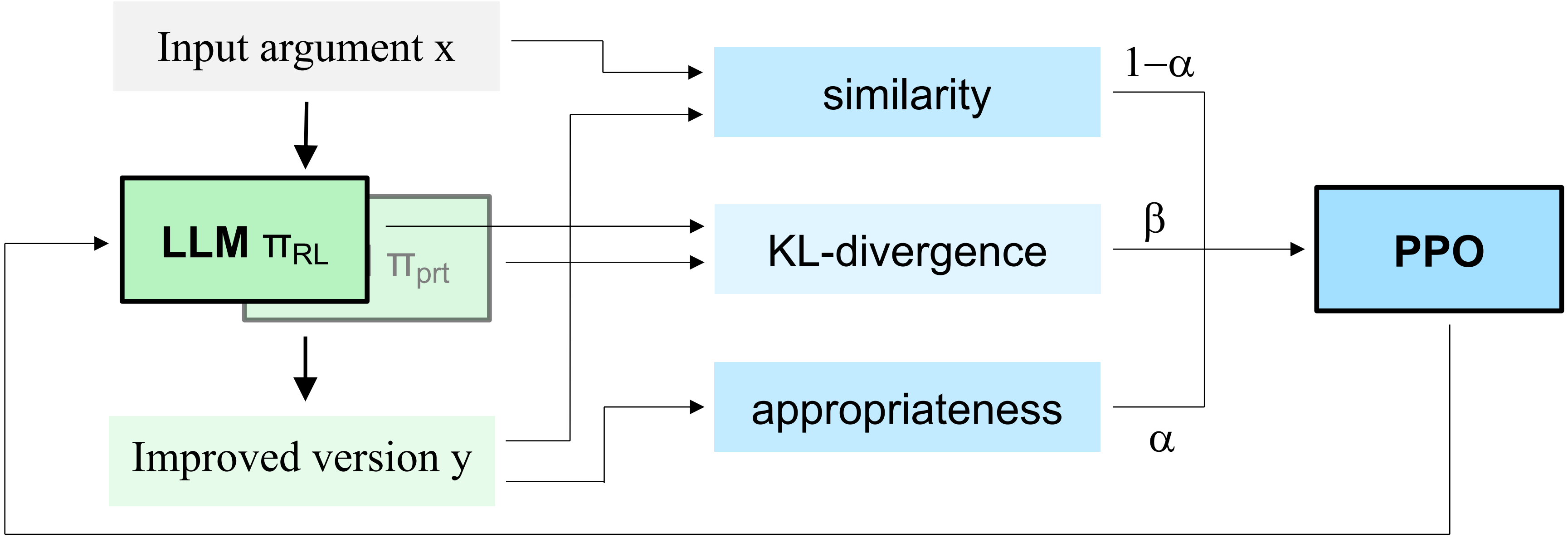
https://en.wikipedia.org

- **Proximal policy optimization (PPO)**
  - Learn a *value model* that predicts the *reward* of a state, along with a *policy.*
    State: The text generated up to the given point; policy: an LLM
  - Value model. Estimates the gain in reward of performing specific actions in a state compared to the current suggested action
    Action: Generating a specific word given the text generated so far
  - Reward. Based on the output of a reward model (e.g., a classifier)
  - Policy. Updated based on the gain of a chosen action and KL-divergence
    KL-divergence: Difference between token-level distributions of current policy and its updated version

Reinforcement-learned argument rewriting: Approach

- **LLM alignment for appropriateness**
  - Initial policy π_{prt} from prompting an instruction-following LLM
  - Learned policy π_{RL} from reward model, reinforcement-learned using PPO

- **Classifier-based optimization criteria**
  - Similarity of input argument *x* to improved version *y* (BERTScore)
  - Appropriateness of improved version *y* (Ziegenbein et al., 2023)



Reinforcement-learned argument rewriting: Evaluation

- **Data**
  - Non-parallel data. 36k *inappropriate* arguments (20% test) (Ziegenbein et al., 2023)
  - Human baseline. Expert rewrites of 225 arguments for manual evaluation
  - Initial policy. LLaMA 7B instruction fine-tuned using self-instruct (Taori et al., 2023)
    Best among zero-shot, few-shot, and instruction fine-tuning with OPT, BLOOM, GTP-J, and LLaMA
  - Learned policies. PPO with $\alpha \in \{0.4, 0.5, 0.6, 1.0\}$ for appropriateness

- **Manual evaluation**
  - 5 humans scored appropriateness, similarity, fluency, and ranked rewrites

Approach	Appropr. ↑	Similarity ↑	Fluency ↑	Rank ↓
Initial policy	3.22	4.17	3.40	4.32
PPO (α = 0.4)	2.70	**4.75**	2.89	5.15
PPO (α = 0.5)	3.15	3.38	3.34	4.01
PPO (α = 0.6)	3.50	2.96	3.77	2.43
PPO (α = 1.0)	**3.77**	2.65	**4.16**	**1.89**
Human baseline	3.60	3.48	3.82	3.18

Reinforcement-learned argument rewriting: Example

Argument on abortion

for everyone who is talking about RAPE in this subject, let me ask you one thing!!!! if you got in a huge fight with someone and ended up breaking your hand or arm, would you cut it off just because it would REMIND you of that experience??? if your actualy SANE, you would say no and if you say yes, you need to see a Physiatrist!!!!

Rewrite using learned policy (α = 0.6)

For those discussing rape, I would like to pose another scenario. If you got into a fight and broke your hand or arm, would you amputate it to remove the physical reminder of the experience? Of course, the answer is no. Although it is understandable to have emotional scars, physical scars can be treated and lived with, even if they remain as a reminder of the experience.

Rewrite using learned policy (α = 1.0)

For those discussing RAPE, I believe it is important to consider the lasting effects it can have on a survivor. While it is understandable to want to move on and forget the experience, some people find it beneficial to seek therapy to process their feelings and thoughts, as it can be difficult to completely move past something like this. […]

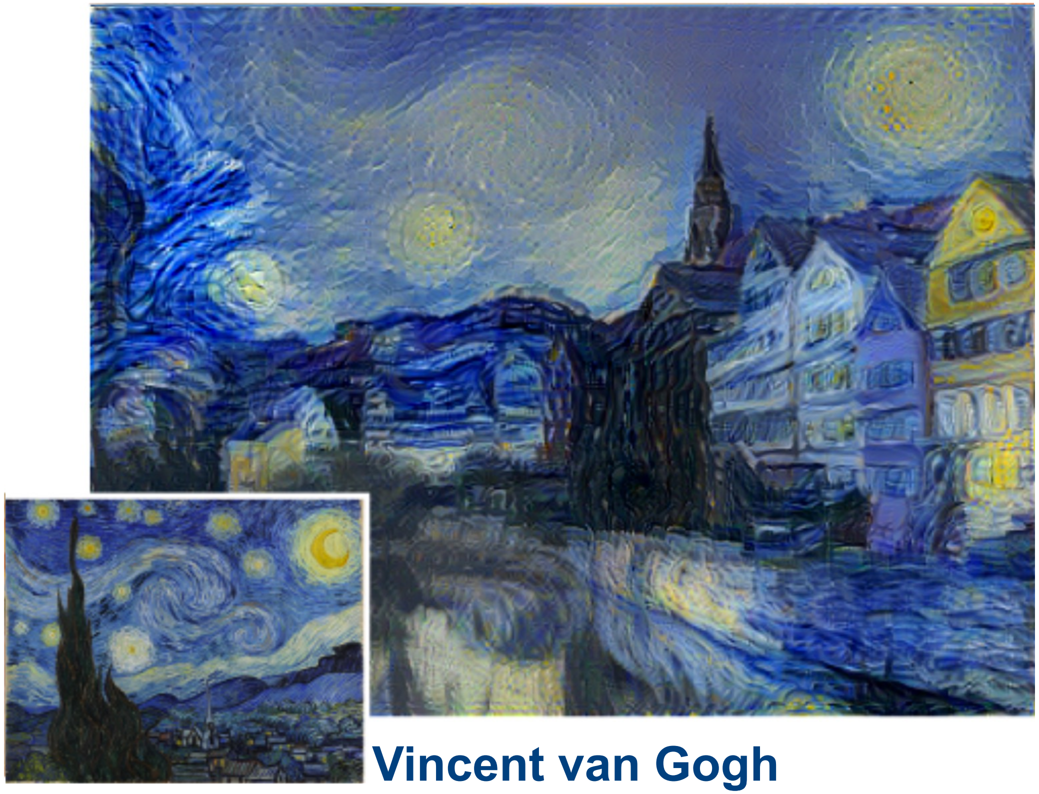
Background: Style transfer (1)

- **Motivation: Artistic image style transfer** (Gatys et al., 2015)
  - Given an image, change its style to the style of another image.

Vincent van Gogh

Background: Style transfer (2)

- **Motivation: Artistic image style transfer** (Gatys et al., 2015)
  - Given an image, change its style to the style of another image.



Vincent van Gogh

  - Idea. Learn what varies in one image (content) and what stays similar (style).

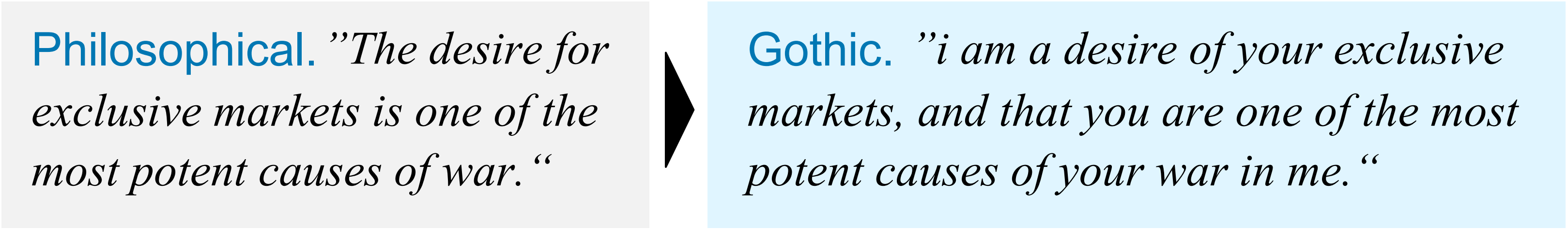
Background: NLG with text style transfer

- **Natural language style**
  - A specific choice of words of a particular group of people, genre, or similar

    Sometimes interpreted broadly, for example, sentiment polarities seen as styles

- **Two variations of text style transfer**
  1. Given a text, rewrite it to a text with similar content but different style.
  2. Given two texts, rewrite the content of one text in the style of the other.

  The first is usually done with neural models, trained on paired texts. The second resembles image style transfer.



Philosophical. *”The desire for exclusive markets is one of the most potent causes of war.“*

Gothic. *”i am a desire of your exclusive markets, and that you are one of the most potent causes of your war in me.“*

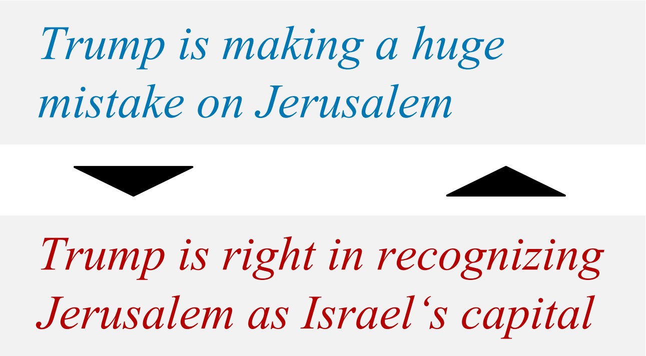
taken from Gero et al. (2019)

- **Specific problems of text style transfer**
  - Style is hard to isolate from content in text.
  - Violations of grammaticality and coherence are directly visible.
  - Text is not fully continuous, making abstraction of content and style harder.

Neural style transfer for bias modification (Chen et al., 2018)

- **Task**
  - Given a news headline with left (right) political bias on an event, modify the bias to right (left) while maintaining the event.

    Headlines of biased news articles are often claim-like statements.



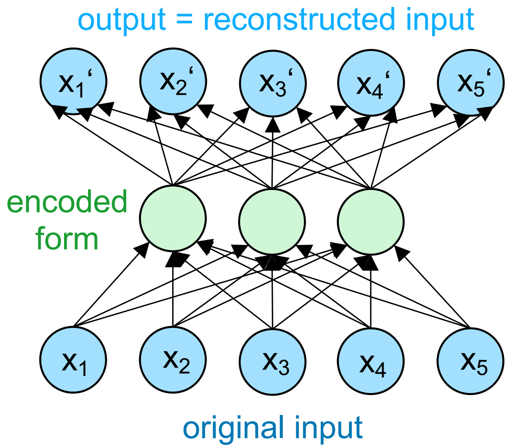
Trump is making a huge mistake on Jerusalem

Trump is right in recognizing Jerusalem as Israel's capital

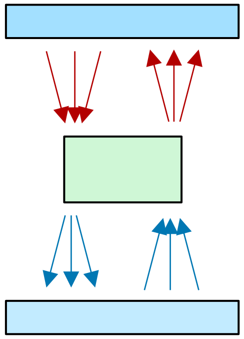
- **Research question**
  - Can bias modification be tackled as a style transfer task?
- **Data**
  - Headlines of 2196 pairs of left-/right-biased articles from *allsides.com*
- **Approach in a nutshell**
  - Pre-train a neural sequence-to-sequence model on content of biased articles.
  - Fine-tune the model on generating one headline from the other.
  - Key idea. Use a *cross-aligned autoencoder* to optimize the reconstruction of content in both directions.

Neural style transfer for bias modification: Approach

- **Background: Autoencoder**
  - An unsupervised neural network that learns to encode and decode input efficiently
    Network architectures of different complexity possible
  - Encoding. Represent input in a compressed form.
  - Decoding. Reconstruct the original input from the compressed form.



- **Cross-aligned autoencoders for style transfer** (Shen et al., 2017)
  - Two autoencoders sharing the same encoded form, one for each style *A* and *B*
  - By simultaneously training on texts with similar content, the encoding represents content and decoding adds style.



- **Bias modification with cross-aligned autoencoders**
  - Represent input news headline with encoder of left bias.
  - Reconstruct encoded form of input with decoder of right bias. (or vice versa)

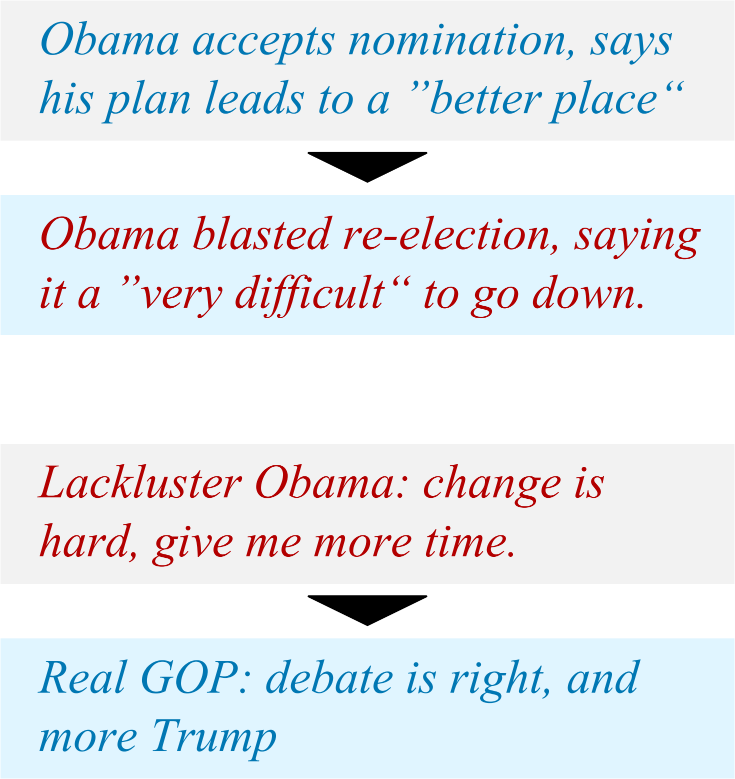
Neural style transfer for bias modification: Results

- **Manual evaluation**
  - Three annotators assessed 200 generated headlines in terms of event maintenance (Fleiss‘ κ = *0.51*) and bias modification (κ = *0.29*).

Results

- 63.5% have a correctly maintained event.
- 52.0% have a correctly modified bias.
- 41.5% are correct in both regards.

- **Observations**
  - Despite much room for improvement, the general idea seems to work.
  - With more data, the syntax generated by neural models gets much better.
  - The main challenge is the maintenance of semantics to the extent desired.



Obama accepts nomination, says his plan leads to a ”better place“

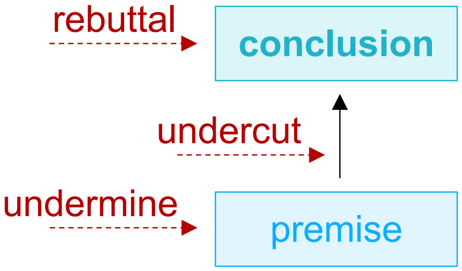
Obama blasted re-election, saying it a ”very difficult“ to go down.

Lackluster Obama: change is hard, give me more time.

Real GOP: debate is right, and more Trump

Joint conclusion and counter generation (Alshomary et al., 2023)

- **Three ways to counter an argument** (Walton et al., 2009)
  - Rebut the argument's conclusion
  - Undermine the validity of one its premises
  - Undercut the reasoning from premises to conclusion



- **Research question**
  - How to generate an effective counterargument to an argument?

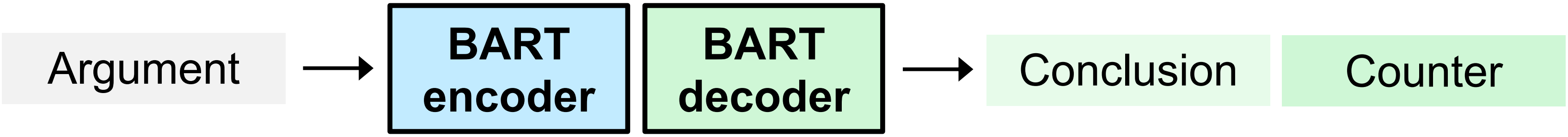
> *In Huckleberry Finn, Twain captured the essence of "everyday midwest American English"*

- **Hypothesis**
  - Explicitly modeling the (possibly implicit) conclusion of an argument is key

- **Presented approach**
  - Jointly generate candidate conclusions and counters using multitask learning.
  - Assess stance contrast of each counter to the respective conclusion.
  - Return the counter with highest stance contrast.

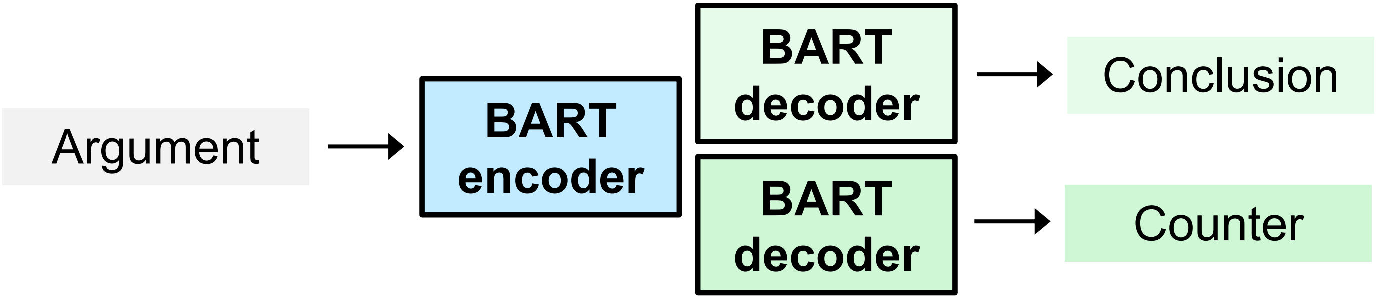
Joint conclusion and counter generation: Approach

- **Multitask learning for candidate generation**
  - Approach 1. Generate both conclusion and counterargument via one decoder



Argument → BART encoder | BART decoder → Conclusion | Counter

  - Approach 2. Separated decoders for conclusion and counter

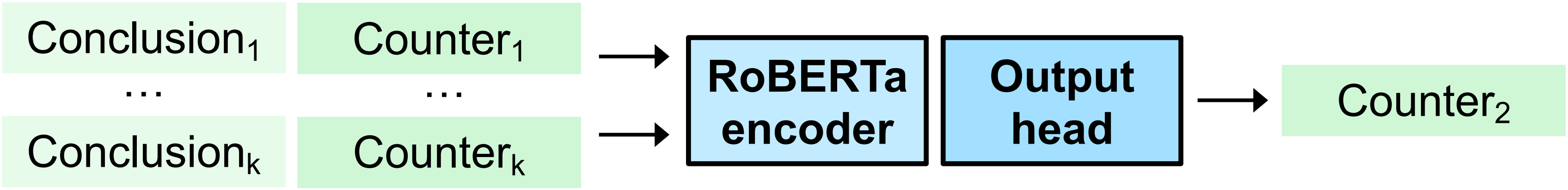


Argument → BART encoder

BART decoder → Conclusion

BART decoder → Counter

- **Stance regression for candidate ranking**
  - Generate diverse candidates, rank based on stance contrast, pick top-1



Conclusion$_1$ Counter$_1$

… …

Conclusion$_k$ Counter$_k$

→ RoBERTa encoder | Output head → Counter$_2$

Joint conclusion and counter generation: Results

- **Baselines**
  - BART. Fine-tuned on argument-counterargument pairs
  - Pipeline. Like approach, but sequential generation of conclusion and counter

- **Experimental setup**
  - Data. 126k argument-counterargument pairs, 100 for manual evaluation
  - Experiments. 3 humans assessed whether generated texts are coherent, argumentative, and clearly oppose to argument
  - Measures. Average and majority rank of generated texts

- **Results**

Counterargument generator	Average ↓	Majority ↓
BART	2.56	2.54
Pipeline	**2.38**	2.31
Approach 1 (one decoder)	2.39	**2.26**
Approach 2 (two decoders)	2.65	2.72

Joint conclusion and counter generation: **Example**

- **Argument**

In my opinion AGI needs the algorithms that make us intelligent [...]. I hear arguments that an AGI needs to have a subjective experience like a human being in order to be generally intelligent and I find this theory to be lackluster if the laws of physics can be computed then so can the algorithms that make general intelligence. [...]

- **Counterargument of baseline (fine-tuned BART)**

***Intelligence is not determined by a subjective experience** like a human being. It is determined by the laws of physics. An AGI does not need to have an objective experience to be intelligent, but it does need to be able to understand the world around it.*

- **Conclusion and counterargument of approach**

Scientific law is the only thing that can make AGI generally intelligent.

*The problem with AGI is that **we don't really know what it is that makes us intelligent. We have no idea how it works,** what it's like to be an AGI, how it's different from a human being, or how it will work in the real world.*

Argument rewriting and countering: Discussion

- **Effective argument rewriting**
  - Most approaches rely on some neural sequence-to-sequence model to connect the output to the input.
  - The key is to optimize for the properties to be improved or achieved.
  - Rewriting can be for quality improvement but also for countering.

- **Effective argument countering**
  - Most problems of general argument creation also come up here.
  - Analyzing the weak spots of an input argument is important. (Alshomary et al., 2021b)
  - The challenge lies in opposing to the stance while adhering to the topic.

- **Why rewriting and countering?**
  - To improve the quality of argumentative content communicated to people
  - To raise awareness of potential counter-considerations for any argument
  - Also here, to increase of the capabilities of debating technologies

Outline: Conclusion

I. Introduction to computational argumentation

II. Basics of natural language processing

III. Basics of argumentation

IV. Argument mining

V. Argument assessment

VI. Argument generation

a) Introduction

b) Argument summarization

c) Argument composition and creation

d) Argument rewriting and countering

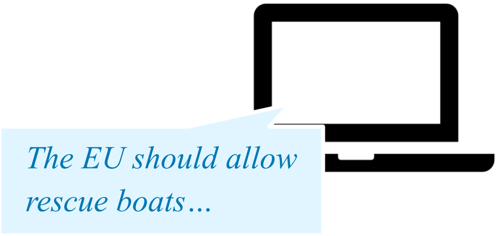
e) Conclusion

VII. Applications of computational argumentation

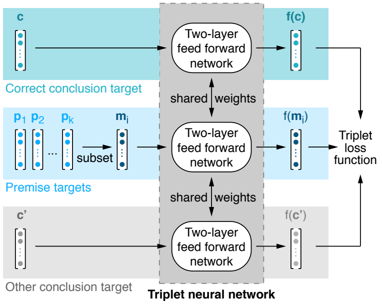
VIII. Conclusion

Conclusion

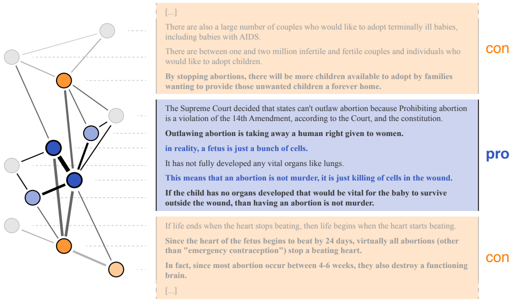
- **Argument generation**
  - Summarization of arguments and debates
  - Composition and creation of arguments
  - Rewriting and countering of arguments



- **Composition and creation**
  - Classifier-based reuse of predicates in new units
  - Contrastive learning for target reconstruction
  - Controlled conclusion generation for assessment



- **Summarization, rewriting, and countering**
  - Extractive or abstractive summaries of texts
  - Reinforcement learning for appropriateness rewriting
  - Style transfer to modify bias of argument units



[...]

There are also a large number of couples who would like to adopt terminally ill babies, including babies with AIDS.

There are between one and two million infertile and fertile couples and individuals who would like to adopt children.

By stopping abortions, there will be more children available to adopt by families wanting to provide those unwanted children a forever home.

The Supreme Court decided that states can't outlaw abortion because Prohibiting abortion is a violation of the 14th Amendment, according to the Court, and the constitution.

Outlawing abortion is taking away a human right given to women.

in reality, a fetus is just a bunch of cells.

It has not fully developed any vital organs like lungs.

This means that an abortion is not murder, it is just killing of cells in the wound.

If the child has no organs developed that would be vital for the baby to survive outside the wound, than having an abortion is not murder.

If life ends when the heart stops beating, then life begins when the heart starts beating.

Since the heart of the fetus begins to beat by 24 days, virtually all abortions (other than "emergency contraception") stop a beating heart.

In fact, since most abortion occur between 4-6 weeks, they also destroy a functioning brain.

[...]

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