Computational Argumentation — Part IV

Argument Mining

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Learning goals

- **Concepts**
  - Major argument models
  - Definitions, goals, and tasks in argument mining

- **Methods**
  - Filtering of argumentative texts
  - Segmentation of argumentative and non-argumentative units
  - Classification of types of argumentative units
  - Identification of relations between units and arguments

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

- **Within this course**
  - The first of three main stages in computational argumentation

Outline

I. Introduction to computational argumentation

II. Basics of natural language processing

III. Basics of argumentation

IV. Argument mining

- **a) Introduction**
- b) Argument models
- c) Unit segmentation
- d) Unit type classification
- e) Relation identification
- f) Conclusion

V. Argument assessment

VI. Argument generation

VII. Applications of computational argumentation

VIII. Conclusion

What is argument mining?

- **Argument mining** (aka argumentation mining)
  - The identification of argumentative structure in natural language text, in terms of units and their relations
  - May be based on different argument models
  - Often, the argument mining process includes multiple steps.

non-argumentative argumentative Conclusion

” 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 rescue boats. Nothing justifies to endanger the life of innocent people.”

support

Premise

support

Premise

- **Why argument mining?**
  - Real-world arguments are often ”hidden“ in longer text, possibly fragmented.
  - Mining provides the basis for any argument analysis and any application.

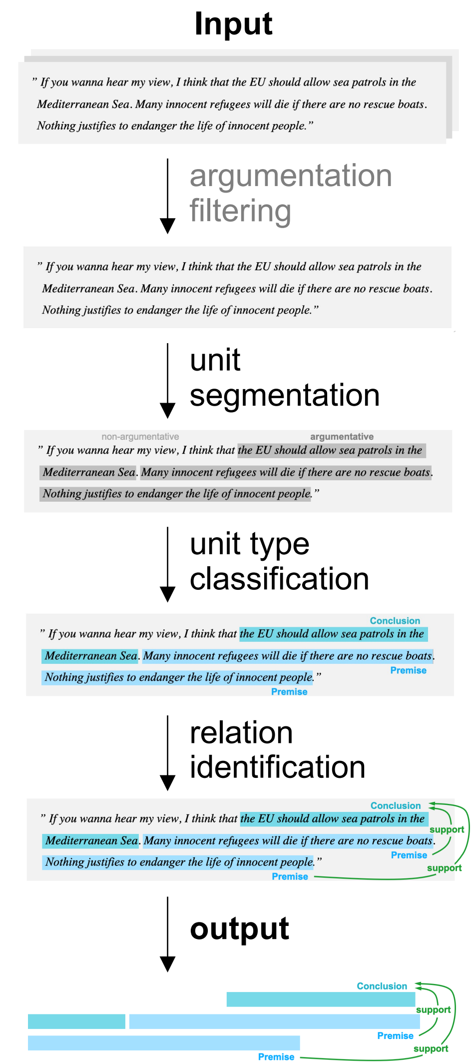
    Exception: Arguments, and their structure, are already given in the source data.

Overview of the argument mining process

- **General process signature**
  - Input. A set of (plain) texts
  - Output. The argumentative structure of each text
    What structure is mined exactly depends on the employed argument model.

- **Main high-level tasks**
  - Argumentation filtering. Finding argumentative texts
  - Unit segmentation. Finding argumentative units
  - Unit type classification. Finding types of units
  - Relation identification. Finding relations between units

- **Notice**
  - Different task decompositions exist in literature.
    Some also see assessment tasks as part of argument mining.
  - The tasks are not always tackled in the given ordering.
  - Not all tasks always need to be tackled.



Next section: Argument models

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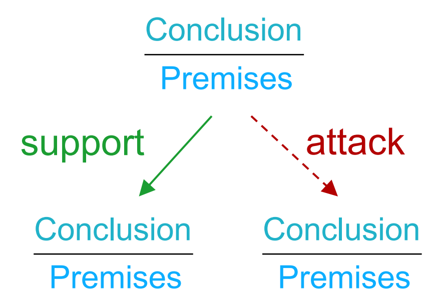
What is an argument model?

- **Argument model**
  - Formalized definition of the concepts distinguished for an argument
  - Concepts usually reflect structural and/or semantic aspects.
  - Used in computational argumentation to operationalize argument processing
    The concepts define the types of meta-information created by mining (and partly assessment) methods.

- **Argument model as a graph**
  - Most models can be represented as a graph *G = (V, E)* with nodes *V* and edges *E.*
  - Labeling/Weighting functions may be given for *V* and *E.*
    We will mostly just use visual representations of the graph elements.



- **Argument models**
  - Several models of arguments have been proposed in argumentation theory and computational research from practice.
  - What model to use depends on the given genre and intended application, i.e., on what the distinguished concepts are meant to be used for.

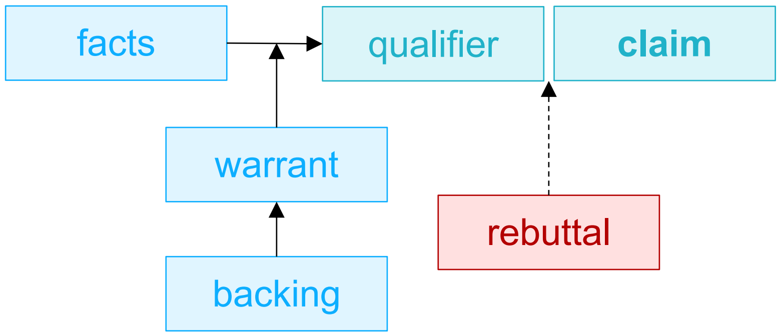
Overview of existing argument models

- **Selected models from theory**
  - Toulmin model. Fine-grained unit roles (Toulmin, 1958)
  - Freeman model. Dialectical exchange of views (Freeman, 2011)
  - Argumentation schemes. Form of inference within an argument (Walton et al., 2008)
  - IBIS. Relations between issues, stances, and arguments (Kunz and Rittel, 1970)
  - Abstract argumentation framework. Attacks between arguments (Dung, 2015)
  - Weighted bipolar argumentation. Support and attack of weighted arguments (Amgoud and Ben-Naim, 2018)

- **Selected models from practice**
  - Essay-specific. Hierarchical relations of claims and premises (Stab, 2017)
  - Editorial-specific. Fine-grained strategy-related unit roles (Al-Khatib et al., 2016)
  - Robust models. e.g., claim on issue, with stance and evidence (Bar-Haim et al., 2017)

- **Notice**
  - Some theoretical models are also used in practice, partly in simplified form.

Toulmin‘s argument model



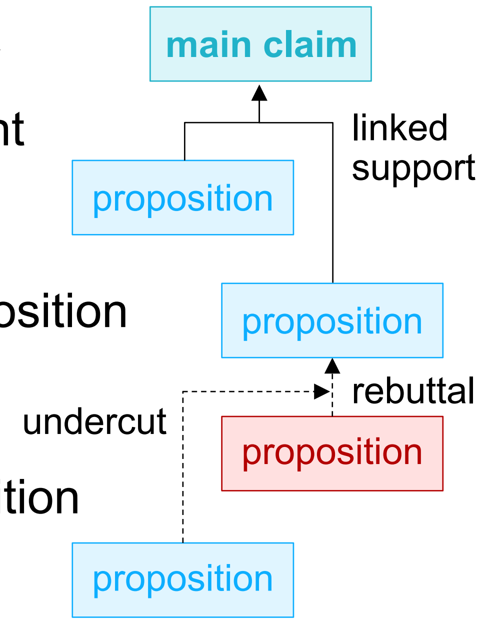
- **Toulmin model** (Toulmin, 1958)
  - Captures an argument‘s internal structure with fine-grained unit roles
    The relation between the roles is clear by definition.

- **Unit types**
  - Claim. A conclusion conveying a stance on the given issue
  - Qualifier. Constraint or uncertainty of the claim
  - Facts (aka data/grounds). Evidence given to support the claim
  - Warrant. Defeasible rule for why the claim can be inferred from the facts
  - Backing. Justification of the warrant
  - Rebuttal. Circumstances under which the claim (or warrant) does not hold
    Backing, qualifier, and rebuttal are optional.

- **Discussion**
  - The model clarifies how arguments work, but few real-life arguments match it.
    Units such as the warrant are often left implicit. Also, units may mix up more than one role.
  - Simplified variants have been used in practice. (Habernal and Gurevych, 2016)

Freeman‘s argument model based on Peldszus and Stede (2013)

- **Freeman model** (Freeman, 2011)
  - Captures the (hypothetical) dialectic exchange in an argument between a proponent defending a claim and an opponent attacking it
- **Unit types**
  - (Main) Claim. The proposition the proponent argues for
  - Proposition. Any other unit of the proponent or opponent
- **Relation types**
  - (Linked) Support. Inference from proposition(s) to proposition
    Peldszus and Stede (2013) consider *example* as a special type of support.
  - Rebuttal. Attack of the acceptability of a proposition
  - Undercutter. Attack of the inference based on a proposition

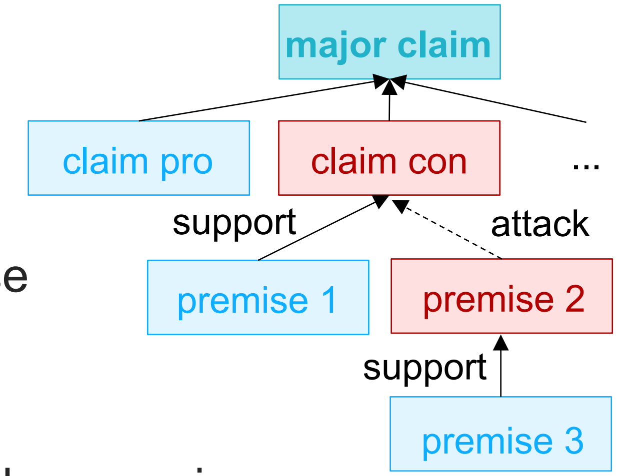


- **Discussion**
  - Freeman aimed to integrate Toulmin‘s ideas with informal logic.
  - In practice, a robust model at least for “clean“ arguments (Peldszus and Stede, 2015)

Essay-specific argument model

- **Essay-specific model** (Stab, 2017)
  - Captures the hierarchical structure of monological argumentative text
- **Unit types**
  - Major claim. The thesis of the text
  - Claim. The conclusion of an argument; has a stance towards the thesis
  - Premise. The premise of a claim or other premise

  Maximum one claim per paragraph



- **Relation types**
  - Support. The support of a claim/premise by another premise
  - Attack. Analog for attacks

  Relations do not cross paragraph boundaries.
- **Discussion**
  - Tuned towards the characteristics and conventions of persuasive essays
  - The assumptions behind may not generalize to many genres

Editorial-specific argument model

- **Editorial-specific model** (Al-Khatib et al., 2016)
  - Captures fine-grained unit roles related to an author‘s argumentation strategy

- **Unit types**
  - Assumption. Claim, fact, or similar that requires justification
  - Common ground. Self-evident fact, accepted truth, ...
  - Anecdote. Example, personal experience, specific event, ...
  - Testimony. Reference to a statement of an expert, authority, ...
  - Statistics. Reference to a finding from a study or similar
  - Other. Any other unit

assumption
common ground
anecdote
testimony
statistics
other

- **Discussion**
  - Tuned towards the characteristics of news editorial argumentation
  - The types encode meaning rather than structural information.
  - The evidence types included are adopted from other models. (Rinott et al., 2015)
  - The ”assumption“ type could benefit from further decomposition.

Next section: Unit segmentation

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What is unit segmentation?

- **Unit segmentation**
  - The segmentation of a text into ADUs, i.e., argumentative units and their non-argumentative counterparts
  - Input. Usually, a plain text (often assumed to be argumentative)
  - Output. All ADUs in the text, defined by their character/token boundaries

non-argumentative **argumentative**

" 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 rescue boats. Nothing justifies to endanger the life of innocent people."

- **How to model that computationally?**
  - Individual classification of candidate start/end character/token boundaries
  - Sequence labeling in terms of BIO tagging of each token in a text (see below)

  ... along with some variations

Example: Unit segmentation of an essay paragraph

- **How good are humans in unit segmentation?**
  - Given the following essay paragraph on "living overseas", identify the ADUs.

> " *Living and studying overseas is an irreplaceable experience when it comes to learn standing on your own feet. One who is living overseas will of course struggle with loneliness, living away from family and friends but those difficulties will turn into valuable experiences in the following steps of life. Moreover, the one will learn living without depending on anyone else.*

example from Stab and Gurevych (2014a)

- **What makes unit segmentation challenging?**
  - What is argumentative may depend on the issue being discussed.
  - Even humans may disagree on the correct segmentation.
  - No clear general definition exists of what makes up the boundaries of ADUs.
    Often, an ADU is a clause or sentence w/o discourse markers, but multiple-sentence ADUs exist (Rinott et al., 2015).

Overview of units and their segmentation

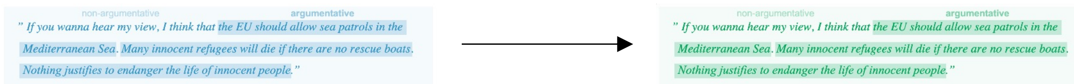
- **Argumentative units across genres**
  - Some genres are very dense in terms of argumentative units.
  - Others have a low proportion only, or argumentativeness is issue-dependent.

- **Argumentative units in selected genres**
  - Persuasive essays. Nearly everything is argumentative. (Stab and Gurevych, 2014a)
  - News editorials. Many ADUs rather have a *rhetorical* role. (Al-Khatib et al., 2016)
  - Wikipedia articles. Argumentativeness is issue-dependent. (Rinott et al., 2015)
  - Forum discussions. Argumentativeness strongly varies. (Habernal and Gurevych, 2017)

- **Selected approaches to unit segmentation**
  - Rule-based unit segmentation using parse trees on essays (Persing and Ng, 2016)
  - Sequence labeling using diverse features on essays (Stab, 2017)
  - Neural argument mining using diverse features on essays (Eger et al., 2017)
  - Cross-genre unit segmentation with various models and features (Ajjour et al., 2017)
  - Contextualized word embeddings with attention on essays (Spliethöver et al., 2019)

Cross-genre unit segmentation (Ajjour et al., 2017)

- **Task**
  - Given a text, classify each token as belonging to an argumentative unit or not.
  - Learn segmentation on one genre, apply on (potentially) another.



- **Research questions**
  1. What features are most effective in unit segmentation?
  2. What model is best to capture relevant context of a token?
  3. To what extent do features and models generalize across genres?

- **Systematic comparison of approaches**
  - Three corpora with texts from different genres
    Basically, all corpora that allowed studying unit segmentation at that time
  - Three machine learning models capturing different context
    The models partly approximate existing approaches, partly realize new ideas.
  - Four feature types capturing different linguistic layers
    The feature types approximate main ideas from previous approaches.

Cross-domain unit segmentation: Corpora

- **Token-level BIO format**
  - Unit segmentation is usually modeled as a BIO tagging task.
  - Each token is beginning (B), inside (I), or outside (O) of an argumentative unit.

" If you wanna hear my view I think that the death penalty should be abolished ."
O O O O O O O O O B I I I I I O

- **Three corpora of different genres**
  - Essays. 402 persuasive student essays, 359.5 tokens/text (Stab, 2017)
  - News editorials. 300 news editorials, 957.9 tokens/text (Al-Khatib et al., 2016)
  - Web discourse. 340 comments etc., 252.9 tokens/text (Habernal and Gurevych, 2015)

- **Corpus preparations**
  - Annotations boiled down to: argumentative or not
  - Represented in BIO format
  - Original train/test splits used

Corpus	B	I	O
Essays	6 089	94 411	44,022
News editorials	14 234	251 381	21 849
Web discourse	1 129	40 042	44 814

Cross-genre unit segmentation: Approaches

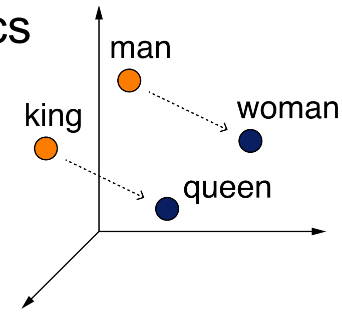
- **What context of a token is important?**

> *" If you wanna hear my view I think that* ***the*** *death penalty should be abolished ."*

- **Machine learning models** (details on Bi-LSTM below)
  - SVM. Linear support vector machine that classifies each token independently
  - CRF. Linear-chain conditional random field that classifies each token in the context of its $k = 5$ surrounding tokens
  - Bi-LSTM. Neural network where Bi-LSTMs capture the entire text as context
- **Token-level feature types**
  - Structural. Indicators whether the token is at the start, inside, or at the end of a sentence, clause, or phrase respectively
  - Syntactic. Part-of-speech tag of the token
  - Semantic. The token's text (for SVM, CRF) or its *embedding* (for Bi-LSTM)
  - Pragmatic. Indicators whether the token is before, beginning, inside, end, or after a discourse marker

Background: Word embedding

- **Word embedding** (aka word vector)
  - A real-valued vector that represents the distributional semantics of a particular word in a high-dimensional space



$$\textit{queen} \rightarrow \mathbf{v}_{\text{queen}} = (0.13, 0.02, 0.1, 0.4, \ldots, 0.22)$$

  - Words that occur in similar contexts have similar embeddings.
    In other words, similarity can be observed even when different words are used.

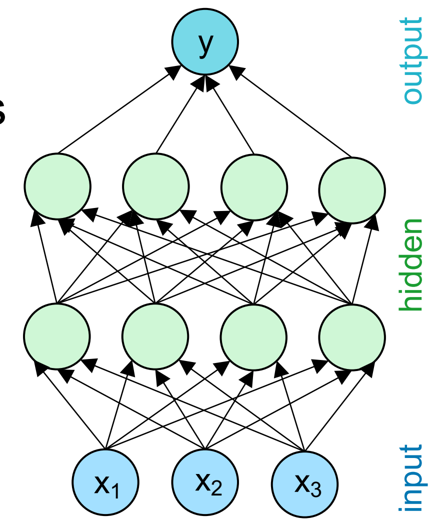
- **Word embedding model**
  - A function that maps each known word to its embedding.
  - Derived from a language model, trained on a (usually huge) corpus

The monarchy is ruled by the ________.

  - Several pretrained embeddings models can be found on the web.
    Examples: Glove, word2vec, Fasttext, Flair, BERT, DeBERTa, …
  - Many embedding models can also be fine-tuned on a given task.

Background: Neural network

- **Neural network in a nutshell**
  - A network of layers of units that takes a set of input values and computes one or more output values.
  - Used for classification or regression in machine learning
  - Units. Compute non-linear weighted sums of input values
    An activation function, such as *tanh,* is applied to weights learned during training.
  - Layers. Multiple layers allow learning complex functions
  - Feed-forward networks. No cycles, fully connected layers

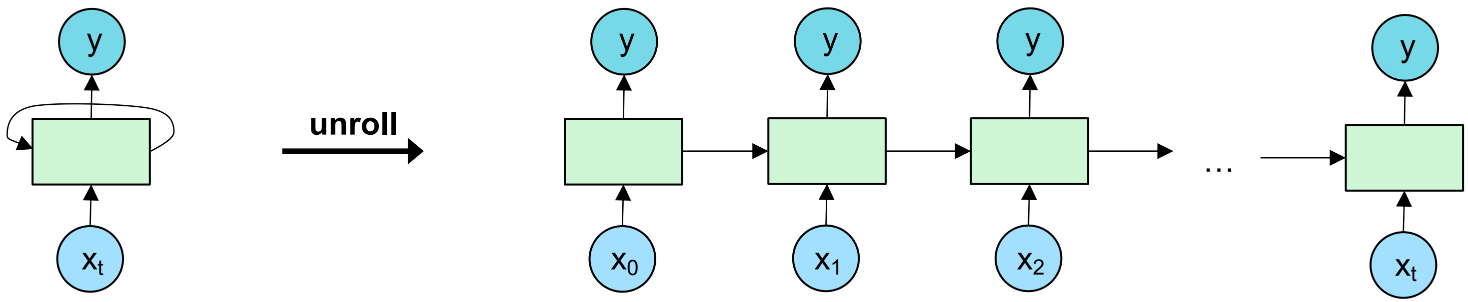


- **Neural networks in NLP**
  - Input tokens are represented in form of word embeddings.
    Other, human-defined features can be encoded as *one-hot vectors.*
  - *Recurrent neural networks* may be used to capture sequential information.
    Later in the course, we also see other architectures such as transformers.

- **Notice**
  - In this course, neural network concepts are detailed only as far as needed.
    For a technical background on neural networks, refer to a machine learning or basic NLP course.

Background: Recurrent neural network based on Jurafsky and Martin (2022)

- **Recurrent neural network (RNN)**
  - A neural network with cycles in its connections, i.e., the value of a unit depends on earlier outputs as an input.



  - A text is processed by presenting one token at a time to the network.
  - The layer from step *i* serves as memory (or context) for decisions in step *j* > *i*.

> *" If you wanna hear my view I think that **the** death penalty should be abolished . "*

- **Limitations of simple RNNs**
  - Unidirectionality. Only past input considered, not future input
  - Limited memory. Long-term dependencies hard to learn

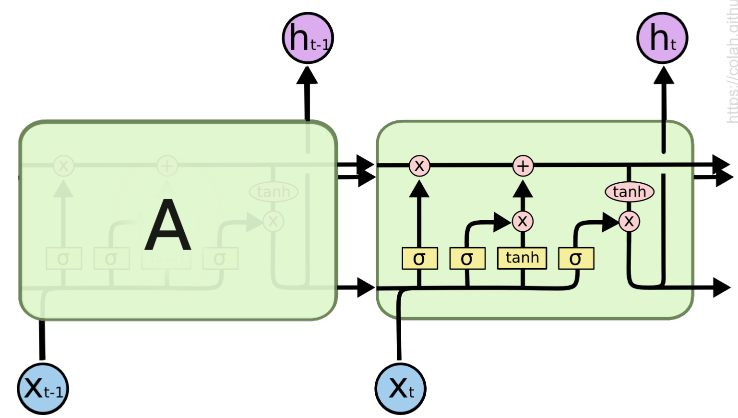
Background: Bi-LSTM neural network

- **Bidirectional RNN**
  - Two RNNs, one processing a text from start to end, the other vice versa

> *" If you wanna hear my view I think that **the** death penalty should be abolished. "*

  - The outputs of the two RNNs are combined into a single representation.
  - By this, an entire input text can be considered as the context of a token.

- **Long short-term memory (LSTM)**
  - Explicit context management in two parts
  - Addition of a context layer to a hidden layer
  - Specialized units that use gates to learn to decide what to forget and what to add for future decisions.



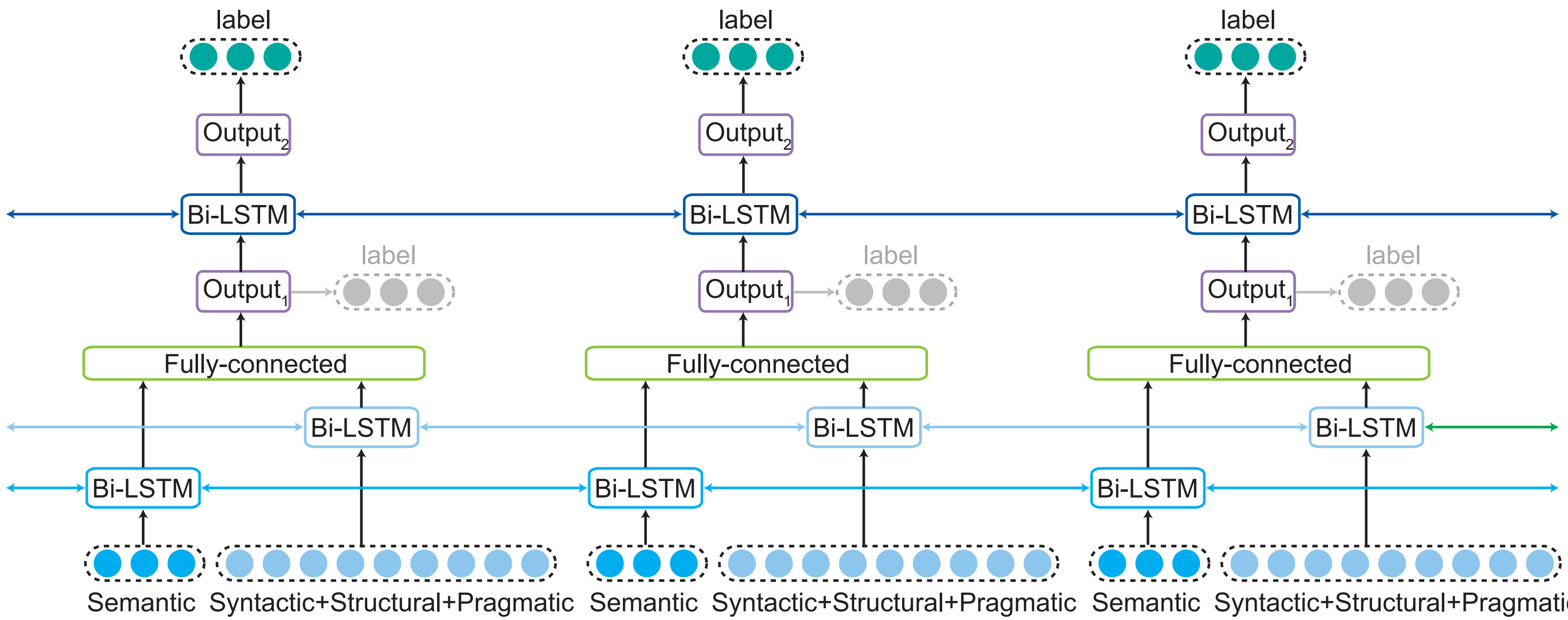
two Bi-LSTM units

- **Bi-LSTM neural network**
  - A bidirectional RNN with LSTM

  Multiple Bi-LSTMs (as well as other neural networks) can easily be stacked.

Cross-genre unit segmentation: Bi-LSTM approach

- **Bi-LSTM unit segmentation approach**



Architecture illustration for three consecutive tokens

- The first Bi-LSTM layers encode semantic features as word embeddings, others as one-hot vectors.
- Another Bi-LSTM layer models dependencies between consecutive tokens.
- Output layers predict confidence values for the possible labels (B, I, O).

Cross-genre unit segmentation: Results

- **Token-level macro F_1-score**
  - All combinations of training and test genre for each approach
    Here, only for *all* features; for details on the features, see the paper of Ajjour et al. (2017).

Approach	Test on essays			Test on news editorials			Test on web discourse		
	Essay	News	Web d.	Essay	News	Web d.	Essay	News	Web d.
SVM	61.4	50.9	31.3	58.8	79.9	**22.6**	**39.1**	37.4	42.8
CRF	79.2	52.5	21.7	**69.8**	82.0	8.0	37.1	**37.6**	37.7
Bi-LSTM	**88.5**	**57.1**	**37.0**	60.7	**84.1**	20.9	20.9	36.6	**54.5**

- **Analysis**
  - 88.5 is significantly better at *p* < *0.001* than best result before (86.7). (Stab, 2017)
  - Bi-LSTM is best, but the others are sometimes better across genres.
  - Semantic features best in-genre (e.g., 87.9 on essays)
  - Structural features most genre-robust (e.g., 35.5–39.5 on web discourse)
  - In general, cross-genre effectiveness limited

Unit segmentation: Discussion

- **Effective unit segmentation**
  - Diverse approaches to unit segmentation may be considered.
  - High effectiveness appears to be possible (only) in narrow explicit genres.
  - The context of a token is critical to assess the token's argumentativeness.

- **Definition of argumentative units**
  - The exact difference to syntactic and discourse units remains to be studied.
  - Depending on the genre, units can span anything from clauses to paragraphs.
  - To some extent, unit segmentation is task-specific.

- **Knowledge required for unit segmentation**
  - It is debatable whether unit segmentation should be tackled first.
  - At this point, no knowledge is given about what is argued about.
  - Joint mining approaches may often be preferable in practice. (Eger et al., 2017)

Next section: Unit type classification

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What is unit type classification?

- **Unit type classification**
  - The assignment of a class to each argumentative unit from a predefined set of classes, in terms of roles within an argument, evidence types, ...
  - Input. A set of argumentative units, often ordered and grouped by input text
  - Output. Each unit with assigned type

Conclusion

" 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 rescue boats.

Premise

Nothing justifies to endanger the life of innocent people."

Premise

- **How to model that computationally?**
  - Supervised text classification of each unit, either feature-based or neural
  - Some approaches tackle unit types as part of relation classification. (more below)

Example: Unit type classification of essay units

- **How good are humans in unit type classification?**
  - Given the following essay units, identify their type (conclusion vs. premise).

Conclusion

"*Living and studying overseas is an irreplaceable experience when it comes to learn standing on your own feet. One who is living overseas will of course struggle with loneliness, living away from family and friends but those difficulties will turn into valuable experiences in the following steps of life. Moreover, the one will learn living without depending on anyone else.*"

Premise

Premise

Premise

example from Stab and Gurevych (2014a)

- **What makes unit type classification challenging?**
  - Unit types may be issue-dependent, e.g., whether a unit is evidence.
  - Positional information is not always as helpful as for essays.
  - Some types encode structural information, others semantics or pragmatics.

Overview of unit types and their classification

- **Unit types across corpora**
  - Unit types may indicate roles, claim and evidence types, or similar.
  - Unit type schemes are model-specific rather than genre-specific.

- **Selected unit type schemes**
  - Argument roles. AAE, WebDiscourse
    (Stab and Gurevych, 2014a; Habernal and Gurevych, 2015)
  - Claim/evidence. IBM Debater, Webis-16-Editorials
    (Rinott et al., 2015; Al-Khatib et al., 2016)

claim premise none major claim

premise rebuttal backing claim pathos

claim study anecdotal expert

assumption statistics anecdote other testimony common ground

- **Selected approaches to unit type classification**
  - Sequence kernels based on words and part-of-speech (Rooney et al., 2012)
  - Supervised classification with rich linguistic features (Stab and Gurevych, 2014a; Habernal and Gurevych, 2015; Rinott et al., 2015; Persing and Ng, 2016; Al-Khatib et al., 2017)
  - Unit-level sequence labeling with rich linguistic features (Habernal and Gurevych, 2017)
  - Tree kernels based on syntactic parse trees (Liga, 2019)
  - Bi-LSTMs based on contextualized word embeddings (Morio et al., 2020)

Supervised classification of evidence types (Al-Khatib et al., 2017)

- **Task**
  - Given editorial units, classify each as being testimony, statistics, anecdote, or none.
- **Approach**
  - Linear SVM on four feature types
  - Lexical. Word *n*-grams
  - Style. Character *n*-grams, length, position, …
  - Syntactic. Part-of-speech *n*-grams
  - Semantic. Entity types, sentiment, …
- **Data**
  - 14k units from 300 editorials (Al-Khatib et al., 2016)
- **Results**
  - Reasonable micro F_1-score, but notable differences across classes

Features	F_1-score
Lexical	0.73
Style	0.70
Syntactic	0.71
Semantic	0.67
All features	**0.77**
Majority baseline	0.56

Class	P	R	F_1
Testimony	0.69	0.40	0.50
Statistics	0.63	0.55	0.59
Anecdote	0.55	0.47	0.51
None	0.84	0.90	0.87

Unit type classification: Discussion

- **Unit type classification**
  - Unit type classification is a fairly standard text classification task.
  - Few existing approaches are really argumentation-specific.
  - Often, segmentation and classification are done jointly, or unit classification is done on the sentence level only.

- **Effectiveness of unit type classification**
  - Effectiveness often rather high; on explicit genres, such as essays (F_1 0.87), as well as on more subtle genres, such as news editorials (F_1 0.77).
    (Stab, 2017; Al-Khatib et al., 2017)
  - Still, minority unit types may be hard to classify accurately.

- **Unit types as roles?**
  - Conceptually, classifying the argumentative *role* of a unit is questionable, because one unit may have different roles in different arguments.
  - Still, role classification works well in narrow genres, such as essays. Why?
    Stab (2017) distinguished major claims, claims, premises, and none.

Next section: Relation identification

What is relation identification?

- **Relation identification**
  - The mining of argumentative relations between pairs of argumentative units and the classification of their types, usually as *support* or *attack*
  - Input. A set of argumentative units in a text, possibly with assigned unit type
  - Output. All mined argumentative relations, with their type

Conclusion

" 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 rescue boats. Nothing justifies to endanger the life of innocent people."

support

Premise

support

Premise

- **How to model that computationally?**
  - Individual classification of candidate unit pairs
  - Identification of the most likely graph induced by all units and relations

  ... among other ways (more below)

Example: Relation identification of essay units

- **How good are humans in relation identification?**
  - Given the following essay units, mine the relations and classify their types.

> ” *Living and studying overseas is an irreplaceable experience when it comes to learn standing on your own feet. One who is living overseas will of course struggle with loneliness, living away from family and friends but those difficulties will turn into valuable experiences in the following steps of life. Moreover, the one will learn living without depending on anyone else.*

attack support attack

example from Stab and Gurevych (2014a)

- **What makes relation identification challenging?**
  - Technically, two tasks need to be solved: mining and type classification.
  - In some genres, related units may be far away from each other.
  - Subtle argumentation leaves relations implicit on purpose.

Overview of relations and their identification

- **Argumentative relations across genres**
  - The idea of support and attack is genre-independent.
  - Some argument models consider different relation sub-types.

- **Relations in selected corpora**
  - Essay-specific model. Support and attack by premises (Stab and Gurevych, 2014a)
  - Freeman‘s model. Linked/Convergent support, example, rebuttal, undercutter (Peldsdzus and Stede, 2013)
  - Walton‘s model. Inference relations of argument schemes (Lawrence and Reed, 2017)

- **Selected approaches to relation identification**
  - Maximum spanning tree on classified roles and functions (Peldszus and Stede, 2015)
  - Supervised classification based on topic and discourse (Nguyen and Litman, 2016)
  - Topic modeling based on inferential topic pairs (Lawrence and Reed, 2017)
  - Structured SVMs and RNNs based on graph structure (Niculae et al., 2017)
  - Transition-based parsing using BERT and LSTMs (Bao et al., 2021)

MST relation identification (Peldszus and Stede, 2015)

- **Task**
  - Given the segmented ADUs of a text, mine relations between the ADUs and classify them as support or attack.

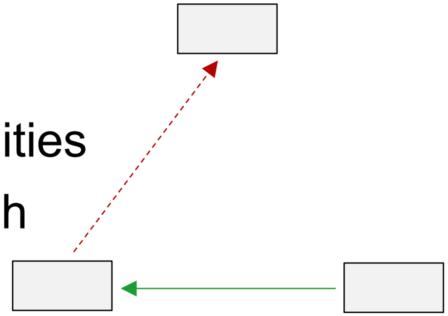
    Peldszus and Stede (2015) study further tasks left out here for simplicity.

- **Research question**
  - Does information about unit types and other argumentative relations in a text help to mine and classify relations?

- **Data**
  - Arg-microtexts. 112 texts with 576 ADUs, annotated for Freeman‘s model
  - The relations are simplified to (single) support and attack.

    290 support, 174 attack, and 2000 ADU pairs w/o relation.

- **Approach**
  - Supervised classifiers to obtain role and function probabilities
  - Weighted probability aggregation to obtain evidence graph
  - Maximum spanning tree (MST) to obtain relations



MST relation identification: Example relations

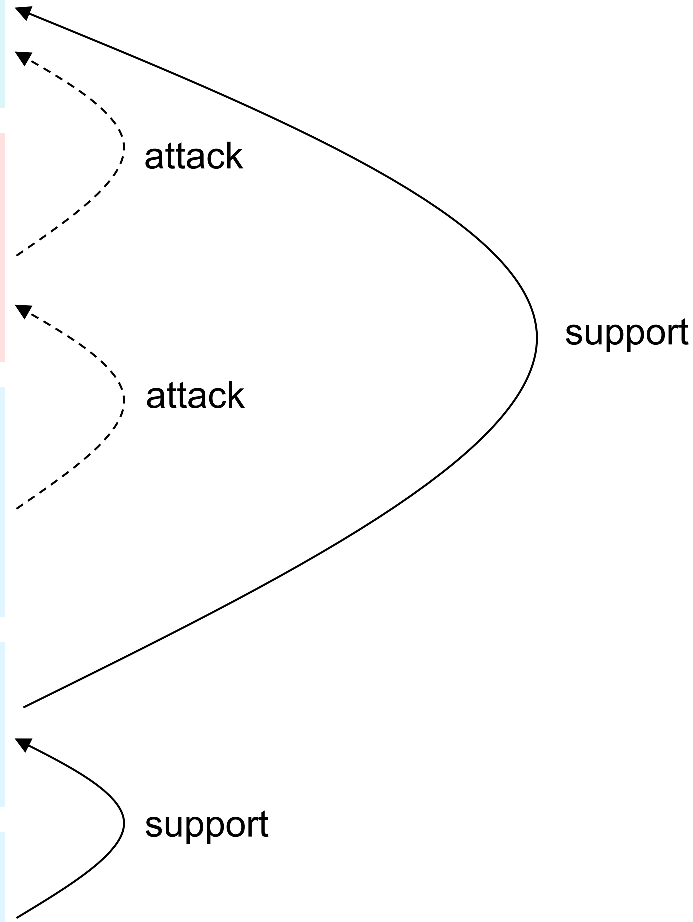
Health insurance companies should naturally cover alternative medical treatments.

Not all practices and approaches that are lumped together under this term may have been proven in clinical trials.

Yet it's precisely their positive effect when accompanying conventional 'western' medical therapies that's been demonstrated as beneficial.

Besides many general practitioners offer such counselling and treatments in parallel anyway

and who would want to question their broad expertise?



MST relation identification: Classifiers and aggregation

- **Supervised classifiers**
  - Role. Predict probabilities of an ADU being proponent (p_p) and thesis (p_t)
  - Function. Predict probability of an ADU being a support (p_s)
  - Relation. Predict probability of an ADU pair being in relation ($p_r^{(i,j)}$)

    A log-loss model with stochastic gradient is used in each case in the experiments.

- **Employed features**
  - Content. Lemma *n*-grams
  - Style. POS tags, main verb morphology, discourse connectives, …
  - Structure. Length of ADU, position in text, …
  - ADU pair. Distance and order of the candidate ADU pair

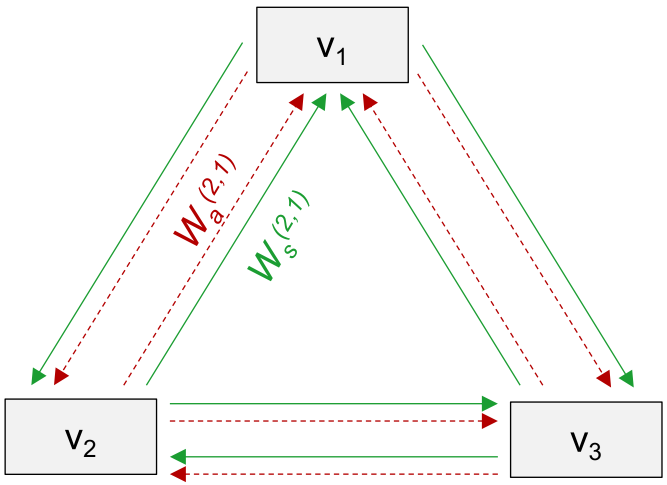
- **Weighted probability aggregation**
  - Each single probability is mapped to a probability $p^{(i,j)}$ for each ADU pair.

    Simple rules; details left out here for simplicity
  - A weighted pair score can be learned in training.

$$w^{(i,j)} = \frac{w_p \cdot p_p^{(i,j)} + w_t \cdot p_t^{(i,j)} + w_s \cdot p_s^{(i,j)} + w_r \cdot p_r^{(i,j)}}{\sum_k w_k}$$

MST relation identification: Evidence graph and MST

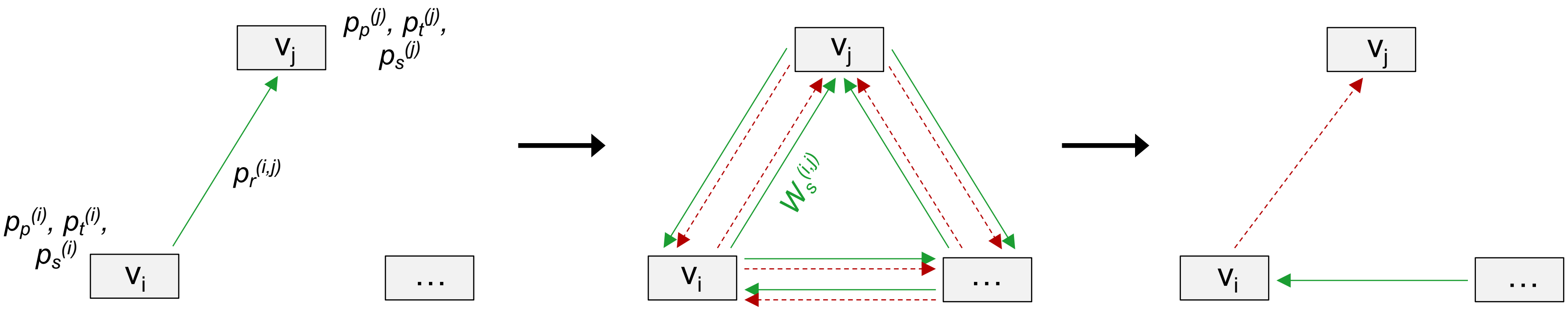
- **Evidence graph**
  - A weighted directed graph $G = (V, E)$
  - Nodes. Each node v in V represents an ADU.
  - Support edges. Any pair of nodes v_i, v_j is connected with an edge e_s.
  - Attack edges. Any pair of nodes v_i, v_j is connected with an edge e_a.
  - Weights. Each e is labeled with a weighted pair score $w^{(i,j)}$ as defined above.



- **Maximum spanning tree (MST)**
  - A sub-graph G^* of a weighted graph $G = (V, E)$ whose edges E connect all nodes V and that has maximum weight
  - Finding an MST can be solved efficiently for directed and undirected graphs.
  - Chu-Liu-Edmonds algorithm. Finds MSTs of directed graphs in $O(E + V \log V)$.
    (Chu and Liu, 1965; Edmonds, 1967)

MST relation identification: Approach and baselines

- **Approach**
  - Apply classifiers and weighted aggregation to build evidence graph.
  - Apply Chu-Liu-Edmonds algorithm to obtain MST.



- **Baselines**
  - Classifiers. Determine whether one ADU supports or attacks another, or not.
  - MST parser. An off-the-shelf discourse parser that uses structured learning to build the MST based on the discourse structure of a text
  - MST parser + classifiers. The MST parser, using the classifiers' outputs as additional features during training

MST-based relation identification: Results

- **Macro F1-score on relation identification**
  - Mining. Source ADU is a premise of target ADU or not
  - Classification. ADU has a supporting or an attacking function

    Jointly trained in 5-fold cross validation, averaged over 10 runs; more results found in Peldszus and Stede (2015)

Approach	Mining	Classification
Classifiers	0.66	0.67
MST parser	0.71	0.49
MST parser + classifiers	**0.72**	0.68
Approach	0.69	**0.71**

- **Analysis**
  - The approach turns out best in classifying relations, but not in mining them.
  - The classifiers also work well with the off-the-shelf MST parser.
  - The MST idea makes sense, if full argumentative structure can be expected.
  - Otherwise, some kind of argument decomposition may be needed before.

Relation identification: Discussion

- **Relation identification**
  - Diverse approaches have been proposed for relation identification.
  - Many works focus on *support*, the default relation from premise to conclusion.
  - Unlike in this lecture part, relations may also be identified for *argument* pairs.

- **Effectiveness of relation identification**
  - Mining relations usually works better than classifying attack vs. support.
  - Semi-reliable for explicit argumentation (Stab, 2017)
  - Unsolved for ”hidden“ argumentation, even hard for humans (Al-Khatib et al., 2017)

- **Difference to stance**
  - Attack/support and pro/con stance classification conceptually overlap.
  - Unlike relations, stance actually refers to the author‘s position on an issue.
  - Still, support/attack can be modeled as pro/con premises with hardly any loss. (Wachsmuth et al., 2017f)

Next section: 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

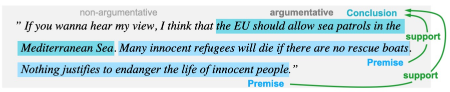
VII. Applications of computational argumentation

VIII. Conclusion

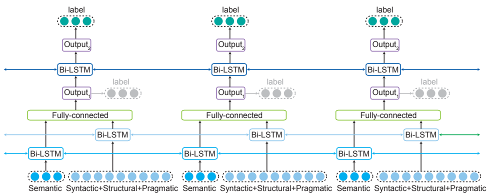
a) Introduction
b) Argument models
c) Unit segmentation
d) Unit type classification
e) Relation identification
f) **Conclusion**

Conclusion

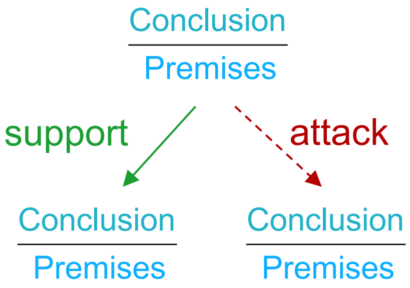
- **Argument mining**
  - Computational identification of argumentative structure
  - May be based on different argument models
  - Segmenting units, classifying types, identifying relations



- **Selected approaches to argument mining**
  - Unit segmentation using rules or Bi-LSTMs
  - Unit type classification using feature-based classifiers
  - Relation identification using MSTs



- **Discussion of argument mining**
  - May work pretty reliable within narrow, explicit genres
  - Hard on subtle argumentation, unsolved across genres
  - Simple argument models may allow more robustness



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