Computational Argumentation — Part V

Resources for Computational Argumentation

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Outline

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Learning goals

- **Concepts**
  - Learn about corpus design principles.
  - Get to know main text corpora for computational argumentation.
  - Get to know other argumentation-related resources.

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- **Methods**
  - Learn how to create a corpus step by step.
  - Understand how to compute agreement between annotators.

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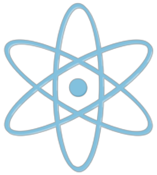
- **Associated research fields**
  - Corpus linguistics
  - Computational linguistics



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- **Within this course**
  - Learn about the use of resources (particularly corpora) in computational argumentation, and understand their concepts.

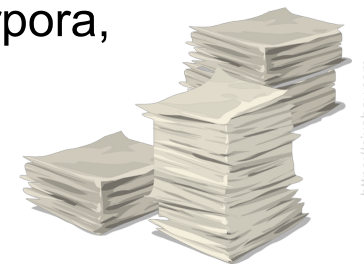
Introduction

What resources?

> *” It’s not the one who has the best algorithm that wins. It’s who has the most data.“*

(Ng, 2018)

- **Data and language resources**
  - In data-driven research, the most important resources are corpora, which form the basis of development and evaluation.
  - We focus *annotated text corpora* for studying argumentation.
  - Other language resources. Lexicons, embedding models, and similar.

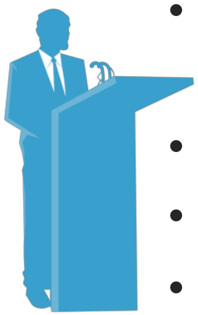


- **Web and software resources**
  - Online debate portals with tons of arguments ”for free”.
  - Community platforms where people collect argument resources.
  - Code libraries for applying computational argumentation.
  - Tools for creating, analyzing, and interacting with arguments.

Argumentative genres (recap)

- **Written monolog**
  - Persuasive essays
  - News editorials / opinionated articles
  - Argumentative blog posts
  - Customer/scientific reviews
  - Scientific articles
  - Law texts

  ... among others



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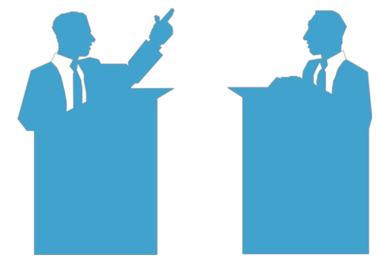
- **Written dialog**
  - Comments to news articles
  - Social media posts
  - Online forum discussions
  - eMail threads
  - Online debates

  ... among others



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- **Spoken monolog** (possibly transcribed)
  - Political speeches
  - Law pleadings

  ... among others

- **Spoken dialog** (possibly transcribed)
  - Classical debates
  - Everyday discussions

  ... among others

- **Notice**
  - The focus in this course is on *written* argumentation, i.e., argumentative texts.

Annotated text corpora (recap)


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- **Text corpus**
  - A collection of real-world texts with known properties, compiled to study a language problem.
  - The texts are often *annotated* with respective meta-information.
  - Corpora are usually split into datasets for developing (training) and/or evaluating (testing) an algorithm.

- **Annotations**
  - Marks a text or text span as representing meta-information of a specific type.
    Annotations may also be called *tags*, *labels*, or similar.
  - Types are specified by an *annotation scheme*.
  - Also used to specify relations between annotations.

Time entity — Organization entity
" 2014 ad revenues of Google are going to reach
Reference — Time entity
$20B. The search company was founded in '98.
Reference — Time entity — Founded relation
Its IPO followed in 2004. [...] "

Topic: "Google revenues" **Genre:** "News article"

- **Corpora in NLP**
  - NLP approaches are developed and evaluated on text corpora.
  - Without, it's hard to develop a good approach, let alone to reliably evaluate it.

Manual, ground-truth, and automatic annotation

- **Manual annotation**
  - The annotations of a text corpus are usually created manually.
  - Annotation may be done by domain or language experts — but also by lay persons, e.g., using *crowdsourcing.*
  - To assess the quality of manual annotations, *inter-annotator agreement* is computed based on texts annotated multiple times.

- **Ground-truth annotations**
  - Manual annotations assumed to be correct are called the ground truth.
  - Sometimes, ground-truth annotations can also be derived from given data using *distant supervision.*
  - NLP algorithms are developed based on analyzing ground-truth annotations.

- **Automatic annotation**
  - Technically, NLP algorithms add annotations of certain types to input texts.
  - The automatic process usually aims to mimic the manual process.

    In this specific lecture, automatic annotation is not in the focus.

Corpus creation

Overview of corpus creation

- **Input**
  - Text compilation. Choose the texts to be included.
  - Annotation scheme. Define what to annotate.
  - Text preprocessing. Prepare texts for annotation.
- **Annotation process**
  - Annotation sources. Choose who provides annotations.
  - Annotation guidelines. Define how to annotate.
  - Pilot annotation. Test the annotation process.
  - Inter-annotator agreement. Compute how reliable the annotations are.
- **Output**
  - Postprocessing. Fix errors and filter annotations.
  - File representation. Store the annotated texts adequately.
  - Dataset splitting. Create subsets for training and testing.

Text compilation

- **Text compilation**
  - The first step in corpus creation is to collect the texts to be included.
  - The compilation should represent the application scenario of the studied task.
  - Several types of potential data bias need to be accounted for.
  - Also, copyrights may have to be considered.

- **Main compilation design decisions**
  - Size. Usually, the more the better, but annotation needs to remain doable.
  - Domains. Topics, genres, languages, etc. (or combinations) to consider.
  - Confounders. Variables to control for (via balancing, range restrictions, ...).
    Examples: Publication time, length, author, as well as many task-specific variables.

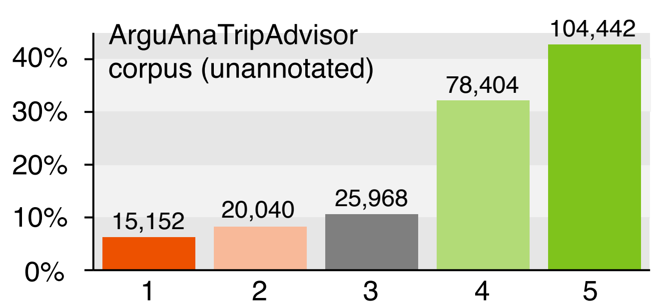
- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - 2100 English hotel reviews to be annotated (+ 196,865 additional).
    All reviews were filtered from a previously published corpus (Wang et al., 2010).
  - 300 reviews each out of 7 locations, 420 each with user overall rating 1–5.
  - At least 10 hotels per location, but as few as possible.

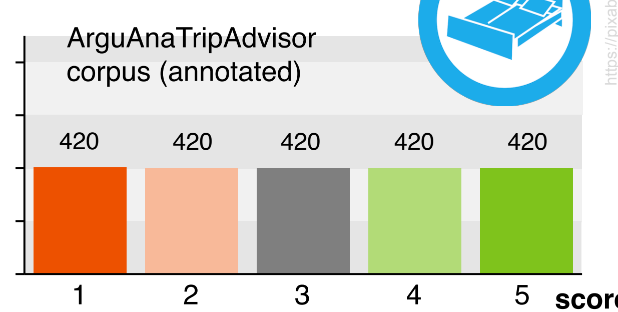
Text compilation: Representativeness and balance

- **Representativeness**
  - A text compilation is representative for some annotation type, if it includes the full range of variability of texts with respect to the type.
  - Representativeness is important for generalization, since the corpus governs what can be learned about a given domain.

- **Representative vs. balanced distributions**
  - Evaluation. The distribution of texts over different values of a type should be representative for the real distribution.
  - Development. A balanced distribution where all values are represented evenly is often favorable (for machine learning and for analysis).

- **Example: ArguAna TripAdvisor corpus**
  (Wachsmuth et al., 2014)





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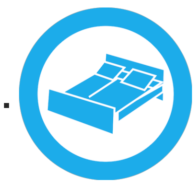
Annotation scheme

- **Annotation scheme**
  - The definition of the annotation types to be considered within a task.
  - Clarifies syntax, semantics, and possibly pragmatics behind each type.
  - Represents the model of the given task and implies what can be studied on a corpus (in a supervised way).

- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - Sentiment. Each statement classified as positive, negative, or neutral.
    A statement was defined to be at least a clause and at most a sentence that is meaningful on its own.
  - Aspects. Each aspect of a hotel marked.
  - Ratings. Each review rated for several quality dimensions.



title: *great* **location**, *bad* **service**

sentiment score: 2 of 5

body: *stayed at the darling harbour holiday inn. The* **location** *was great, right there at China town, restaurants everywhere, the monorail station is also nearby. Paddy's market is like 2 mins walk.* **Rooms** *were however very small. We were given the 1st floor* **rooms**, *and we were right under the monorail track, however* **noise** *was not a problem.* **Service** *is terrible.* **Staffs** *at the* **front desk** *were impatient, I made an enquiry about* **internet access** *from the* **room** *and the person on the phone was rude and unhelpful. Very shocking and unpleasant encounter.*

Text preprocessing

- **Text preprocessing**
  - The preparation of corpus texts for their manual annotation.

- **Usual preprocessing steps**
  - The input files are converted into a common, usually simple format.
  - Metadata is stored, in case it is considered relevant
  - The texts are analyzed, usually automatically, in order to create the instances to be annotated.

- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - Originally, the input reviews were crawled HTML pages.
    Due to the resort to an existing corpus, the reviews had an intermediate format already.
  - The review contents were converted to plain text.
  - The review ratings and other metadata was stored in annotations.
  - Each text was then automatically segmented into statements using a rule-based algorithm provided with the corpus.

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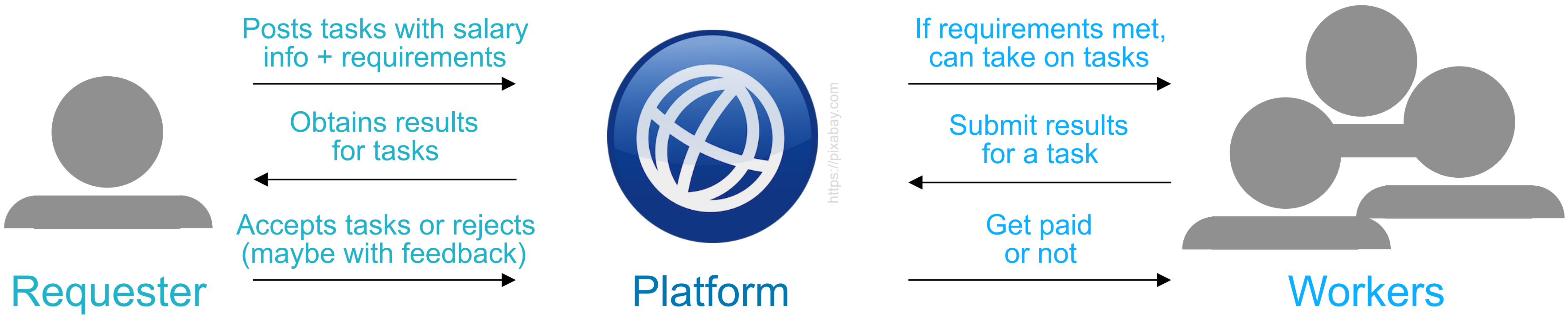
Annotation sources

- **Expert annotation**
  - Experts for a task (or for linguistics, ...) manually annotate each corpus text.
  - Usually achieves the best results, but is often time and cost-intensive.
- **Crowd-based annotation**
  - Instead of experts, *crowdsourcing* is used to create manual annotation.
  - Access to many lay annotators (cheap) or semi-experts (not too cheap).
  - Distant coordination overhead; results for complex tasks unreliable.
- **Distant supervision**
  - Annotations are (semi-) automatically derived from existing metadata.
  - Enables large corpora, but annotations may be noisy.
- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - Sentiment. Crowd-based annotation, with three annotators each.
  - Aspects. Expert annotations, one expert per review (two for a sample).
  - Ratings. Distant supervision; ratings directly obtained from review metadata.

Annotation sources: Crowdsourcing

- **Crowdsourcing**
  - Outsourcing of (usually micro) jobs to people around the world.
  - Tasks and results are submitted to a crowdworking platform.

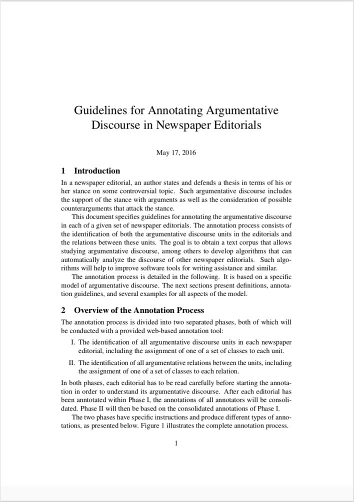


- **Major platforms**
  - mturk.com (Amazon Mechanical Turk, AMT). Biggest platform, lay workers.
  - figure-eight.com (prev. *Crowdflower*). Similar to AMT, some other features.
  - upwork.com (prev. *oDesk*). Semi-professional workers for several areas.

- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - AMT, $0.05 per 12 sentiment classifications, 328 workers involved.

Annotation guidelines

- **Annotation guidelines**
  - To obtain reliable annotations, annotators get guidelines that clarify what and how to annotate.
  - Guidelines define concepts, explain the annotation scheme, prescribe the annotation process, and often give examples.
    Guidelines for experts may span dozens of pages, for lay persons they are often short.



Guidelines for Annotating Argumentative Discourse in Newspaper Editorials

May 17, 2016

1 Introduction

In a newspaper editorial, an author states and defends a thesis in terms of his or her stance on some controversial topic. Such argumentative discourse includes the support of the stance with arguments as well as the consideration of possible counterarguments that attack the stance.

This document specifies guidelines for annotating the argumentative discourse in each of a given set of newspaper editorials. The annotation process consists of the identification of both the argumentative discourse units in the editorials and the relations between these units. The goal is to obtain a text corpus that allows studying argumentative discourse, among others to develop algorithms that can automatically analyze the discourse of other newspaper editorials. Such algorithms will help to improve software tools for writing assistance and similar.

The annotation process is detailed in the following. It is based on a specific model of argumentative discourse. The next sections present definitions, annotation guidelines, and several examples for all aspects of the model.

2 Overview of the Annotation Process

The annotation process is divided into two separated phases, both of which will be conducted with a provided web-based annotation tool:

I. The identification of all argumentative discourse units in each newspaper editorial, including the assignment of one of a set of classes to each unit.

II. The identification of all argumentative relations between the units, including the assignment of one of a set of classes to each relation.

In both phases, each editorial has to be read carefully before starting the annotation in order to understand its argumentative discourse. After each editorial has been anntotated within Phase I, the annotations of all annotators will be consolidated. Phase II will then be based on the consolidated annotations of Phase I.

The two phases have specific instructions and produce different types of annotations, as presented below. Figure 1 illustrates the complete annotation process.

1

- **Length as a design decision**
  - The more detailed, the more guidelines will represent the authors‘ view.
  - The more concise, the more they will represent the annotators‘ view.

- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - For crowd-based sentiment, we had the following simple guidelines:
    (along with a set of carefully chosen examples)

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”When visiting a hotel, are the following statements positive, negative, or neither?“

Notes. *(1)* Pick “neither” only for facts, not for unclear cases. *(2) Pay attention to subtle statements where sentiment is expressed implicitly or ironically. (3) Pick the most appropriate answer in controversial cases.*

Pilot annotation

- **Pilot annotation**
  - Before a complete corpus is annotated, annotation guidelines are usually tested on a small sample.
  - The goal is identify unclear guidelines, overseen and hard cases, as well as general problems.
  - Guidelines are often written incrementally based on multiple pilot studies.
    The cases identified from pilot studies often serve as examples in the guidelines.

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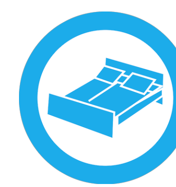
- **Annotators in pilot study**
  - Rule of thumb. If authors don‘t achieve *agreement*, annotators won‘t either.
    In (Al-Khatib et al., 2016b), the annotation of argumentative relations were dropped for this reason.
  - Experts may discuss and align their anntotation based on pilot results.
  - Sometimes, the actual corpus annotators are chosen based on their results.

- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - Sentiment. The guideline above was best among multiple variations.
  - Aspects. The decision to use experts was based on pilot crowdsourcing tests.



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Inter-annotator agreement

- **Inter-annotator agreement** (aka *inter-rater reliability, inter-coder agreement*, ...)
  - A quantification of the similarity of annotations of the same instances by two or more annotators.
    Common numbers of annotators are 2, 3, or 5. Sometimes, also way more are used (especially in crowdsourcing).
  - Usually between 1.0 (total agreement) and –1.0 (systematic disagreement).
    0.0 then means random/no agreement.

- **Why inter-annotator agreement?**
  - Captures the reliability (or homogeneity) of the annotations of a corpus.
  - Gives a rough idea of how effective an algorithm may become.
    It is unlikely that an algorithm will more agree with humans than they agree with each other.
  - Dilemma. Low agreement may indicate bad guidelines or insufficient training — but also just a subjective task.

- **Basis for computing agreement**
  - Either, each corpus instance is annotated by multiple annotators.
  - Or, a sample is annotated multiple times, and the rest once each.
    The former is statistically more reliabile and allows annotation filtering, majority agreement, ...; the latter is cheaper.

Inter-annotator agreement: Overview of measures

- **Joint probability measures**
  - Simply represent percentages of agreement on nominal annotations.
  - Percentage. Proportion of instances where pairs of annotators agreed.
  - Full. Proportion of instances where $k \geq 3$ annotators all agreed.
  - Majority. Proportion of instances where >50% of the annotators agreed.

- **Chance-corrected measures**
  - More robust, taking into account that agreement may be due to chance.
  - Cohen‘s κ. Difference between observed and chance agreement. (see below)
  - Fleiss‘ κ. ”Generalization“ of Cohen‘s κ to $k \geq 3$ annotators.
  - Krippendorff‘s α. Focus on *dis*agreement cases, any *k*, any type of scale.

- **Correlation measures**
  - Quantify the (mean) pairwise correlation among annotators for ordinal scale.
  - Kendall‘s τ. Concordance of ranks of two orderings of instances.
  - Spearmans‘s ρ. Monotonicity of the relation between two orderings.
  - Pearson‘s *r*. Linear correlation between two sets of *continuous* values.

Inter-annotator agreement: Kappa computation

- **Cohen's κ**
  - Given *n* instances annotated by annotators A and B for a set of nominal categories *C*:

$$\kappa = \frac{p_o - p_e}{1 - p_e} \quad \text{where} \quad p_e = \frac{1}{n^2} \sum_{c \in C} a_c \cdot b_c$$

  - p_o is the observed percentage agreement on all instances,
  - p_e is the expected chance agreement, and
  - a_c and b_c are the numbers of times *A* and *B* chose class *c* respectively.

κ range	Agreement
[-1.0, 0.0]	No
(0.0, 0.2]	Slight
(0.2, 0.4]	Fair
(0.4, 0.6]	Moderate
(0.6, 0.8]	Substantial
(0.8, 1.0]	„Perfect"

- **Example**
  - $n = 100$, two categories *c* and *c'*, $p_o = 0.75$, $a_c = b_c = 80$, $a_{c'} = b_{c'} = 20$.

$$p_e = \frac{1}{10000} \cdot (6400 + 400) = 0.68 \quad \text{and thus} \quad \kappa = \frac{0.75 - 0.68}{1 - 0.68} \approx 0.22$$

- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - Sentiment. Fleiss' κ = 0.67 (substantial), 73.6% full, 98.3% majority.
  - Hotel aspects. Cohen's κ = 0.73 (substantial, based on 546 cases).

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Postprocessing

- **Postprocessing**
  - The consolidation of the annotated texts for the final corpus.
  - Includes the *cleansing* of potentially wrong or inconsistent cases.
  - May be manual and/or automatic.

- **Common postprocessing steps**
  - A resolution (or discarding) of cases where annotators disagreed.
  - The removal of noise in the data observed during annotation.
  - The merging of labels (etc.) that have been assigned only rarely with others.
  - The conversion of the instance format into the final corpus *file representation*.

- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - Each statement was assigned its majority sentiment where available.
  - The 1.7% sentiment disagreement cases were resolved manually in the context of their associated reviews.
  - Wrong hotel aspect annotation boundary errors were automatically fixed.

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File representation

- **File representation**
  - Usually, each text in a corpus is stored in a separated file.
    Often, each dataset (or other subset of the corpus) in a separated folder.
  - Large corpora may be stored in databases or indexes.
  - Various file formats and instance representations are used.

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- **Common corpus formats**
  - Plain text file only. One line per token, one tab per token-level annotation.
  - Plain text + annotation file. Only text in file, extra file specifies annotations.
  - XMI/XML file. One file for each text, one tag per annotation.
  - Spreadsheet. One line per text, one column per text/annotation.

- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - XMI files preformatted for the Apache UIMA framework.
  - Each annotation is stored as a tag with attributes and character indices.
  - The annotation scheme is specified in a global type system descriptor file.

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Dataset splitting

Training

Validation

Test

- **Dataset splitting**
  - The decision how to split a corpus into training, validation, and test set (or similar) is not trivial, but depends on the task.
  - The goal is to mimic the real-world situation to be studied.
  - A good split minimizes bias that can be exploited in learning.
  - The annotations within a text should usually not be put in different datasets, as they naturally overlap in terms of content (explicitly or implicitly).
- **Common splitting criteria**
  - Random. The split is done (pseudo-) randomly.
  - Topic. The datasets are (more or less) disjunct in terms of topic.
  - Time. The oldest texts for training, the newest for testing.
  - Other. A split by any other metadata relevant in the given task.
- **Example: ArguAna TripAdvisor corpus** (Wachsmuth et al., 2014)
  - Location. 3 locations for training, 2 for validation, 2 for test.

    This way, location-specific information that may influence sentiment cannot be exploited.

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Amsterdam, Seattle, Sidney

Berlin, San Francisco

Barcelona, Paris

Available Argumentation-related resources

Overview of argumentation-related corpora 1

- **Argumentation-related corpora**
  - Corpora with annotations of argumentative structure.
  - Corpora with assements of argumentation quality.
  - Corpora with classification of stance or similar.

  ... and possibly others

- **Selected corpora on argument structure**
  - AAE-v2. Persuasive essays, proprietary model (Stab, 2017)
  - Arg-microtexts. Short texts, Freeman model (Peldszus and Stede, 2015)
  - Araucaria. Mixed argumentative texts, Walton‘s schemes (Reed and Rowe, 2004)
  - AZ. Scientific articles, argumentative zones (Teufel, 1999)
  - IBM Debater. Wikipedia articles, claims and evidence (Rinott et al., 2015)
  - Web discourse. Mixed web arguments, Toulmin model (Habernal and Gurevych, 2015)
  - Webis-Debate-16. Debate portal arg‘s, argumentativeness (Al-Khatib et al., 2016a)
  - Webis-Editorials-16. News editorials with six unit types (Al-Khatib et al., 2016b)

  ... and some others

Overview of argumentation-related corpora 2

- **Selected corpora on argumentation quality**
  - ArgQuality. Debate portal arguments, 15 quality scores (Wachsmuth et al., 2017b)
  - Cornell ChangeMyView. Discussion posts, effectiveness labels (Tan et al., 2016)
  - UKP-ConvArg. Debate portal arg‘s, convincingness pairs (Habernal et al., 2016)
  - Webis-ArgRank-17. Mixed arguments, relevance rankings (Wachsmuth et al., 2017a)
  - Webis-Editorials-18. News editorials, effectiveness ratings (El Baff et al., 2018)

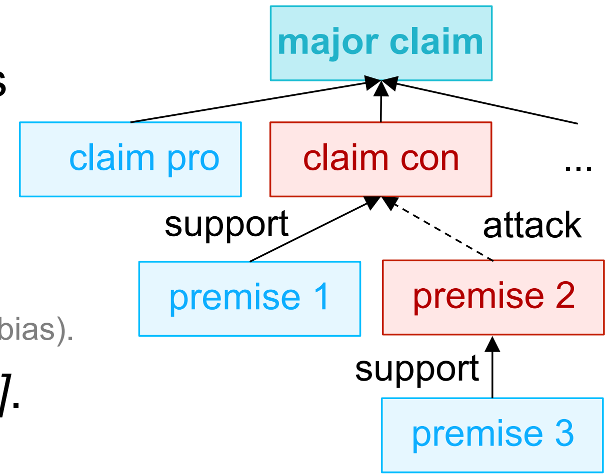
  ... and some others

- **Selected corpora on stance and similar**
  - ArguAna Counterargs. Debate portal counterargument pairs (Wachsmuth et al., 2018a)
  - ArguAna TripAdvisor. Hotel reviews with sentiment flows (Wachsmuth et al., 2014)
  - IBM Debater. Wikipedia articles, claim-related stance (Bar-Haim et al., 2017)
  - Ideological debates. Online discussions with stance (Hasan and Ng, 2013)
  - Internet arguments. Web discussions with topic and stance (Walker et al., 2012)

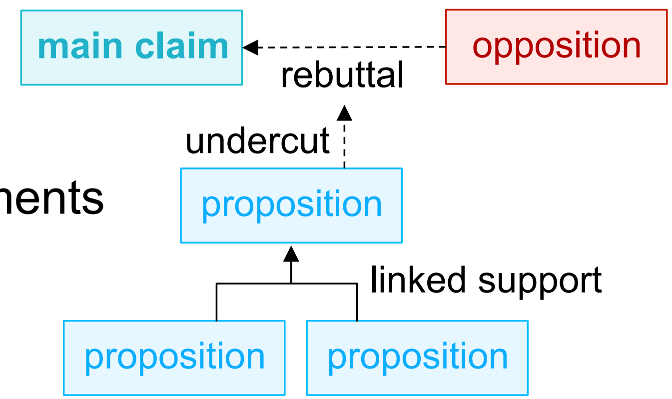
  ... and many others

Examples: AAE-v2 and Arg-microtexts

- **AAE-v2** (Stab, 2017)
  - Texts. 402 mixed-topic persuasive student essays from a web portal.
  - Annotations. 6089 argumentative units of three types and 5687 relations of two types.
    Extensions also cover quality-related annotations (sufficiency and myside bias).
  - Creation. 3 experts, Krippendorff's $\alpha \in [0.63, 0.88]$.



- **Arg-microtexts** (Peldszus and Stede, 2015)
  - Texts. 112 "pure" arguments, explicitly written for 18 different controversial issues.
  - Annotations. 576 units composed in 443 arguments according to Freeman's model.
    Extensions also cover RST discourse structure.
  - Creation. 3 experts, Fleiss $\kappa = 0.83$.



Examples: IBM Debater and Webis-16-Editorials

- **IBM Debater** (Rinott et al., 2015; Bar-Haim et al., 2017)
  - Texts. 2394 claims and 3057 evidence statements for 58 controversial issues from Wikipedia articles.
  - Annotations. Stance of claims towards issue, target in each claim, claim-evidence support relations.
  - Creation. 5 annotators for most parts, mean Cohen‘s κ = *0.4* for claims, *92.5%* majority agreement for target, rest not explicitly reported.

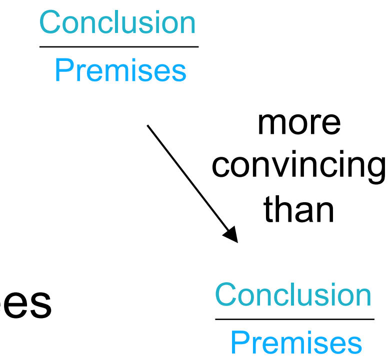
pro claim	55%
con claim	45%
anecdotal	12%
expert	58%
study	31%

- **Webis-16-Editorials** (Al-Khatib et al., 2016)
  - Texts. 300 mixed-topic news editorials, 100 each from three very different online news portals.
  - Annotations. 14,313 argumentative units of six types.
  - Creation. 3 semi-professional crowdworkers each, Fleiss‘ κ = *0.56*, ranging from *0.11* to *0.68.*

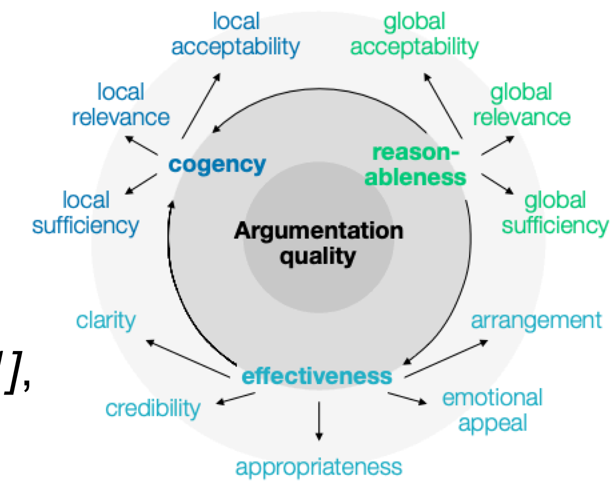
assumption	68%
common ground	2%
anecdote	18%
testimony	8%
statistics	3%
other	1%

Examples: UKP-ConvArg and ArgQuality

- **UKP-ConvArg** (Habernal et al., 2016)
  - Texts. 16,927 argument pairs (based on 1052 arguments) for 32 issue-stance pairs from a debate portal.
  - Annotations. Each pair annotated as to which argument is more convincing (+ free text reasons).
  - Creation. Five lay crowdworkers each, best annotator agrees in 93.5% of the cases with ”majority“. (Hovy et al., 2013)



- **ArgQuality** (Wachsmuth et al., 2017b)
  - Texts. 320 arguments from UKP-ConvArg, 10 each per issue-stance pairs.
  - Annotations. Scores in {1, 2, 3} for 15 different quality dimensions.
  - Creation. 3 experts, Krippendorff‘s $\alpha \in [0.26, 0.51]$, majority agreement $\in [0.87, 0.98]$.

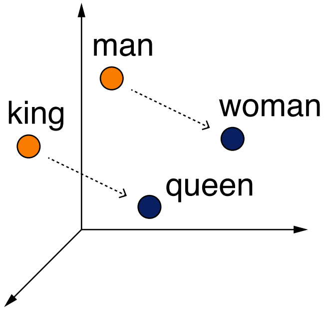


Other language resources

- **Argumentation-related lexicons**
  - Term repositories capturing specific aspects of argumentative language.
  - Often come with much useful meta information.
  - Often can be created from annotated corpora.
    Notice, though, that lexicon generation is a research area itself.

- **Lexicon types**
  - Argument-specific. Still rare and often published only as part of a code library.
    Example: www.hlt.utdallas.edu/~persingq/ICLE/ (lexicons related to argumentation in persuasive essays).
  - Subjective language. Some powerful lexicons exist that include sub-lexica related to argumentation.
    Examples: https://liwc.wpengine.com, http://www.wjh.harvard.edu/~inquirer/

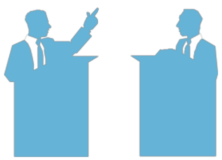
- **Argumentation-related embedding models**
  - Mappings from words, arguments, etc. to real-valued vectors.
  - Still don't exist, mainly due to data sparsity.



Online debate portals

- **Online debate portals**
  - Platforms where arguments are directly given for debates on several issues.
  - Constitute a rich source of ”ground-truth“ argumentation.
    Our argument search engine https://args.me and several corpora are based on debate portal arguments.

- **Two types of portals**
  - Debating forums. In each debate, users argue against each other.
    Examples: debate.org, reddit.com/r/changemyview/, createdebate.com, theworlddebating.com



https://de.wikipedia.org

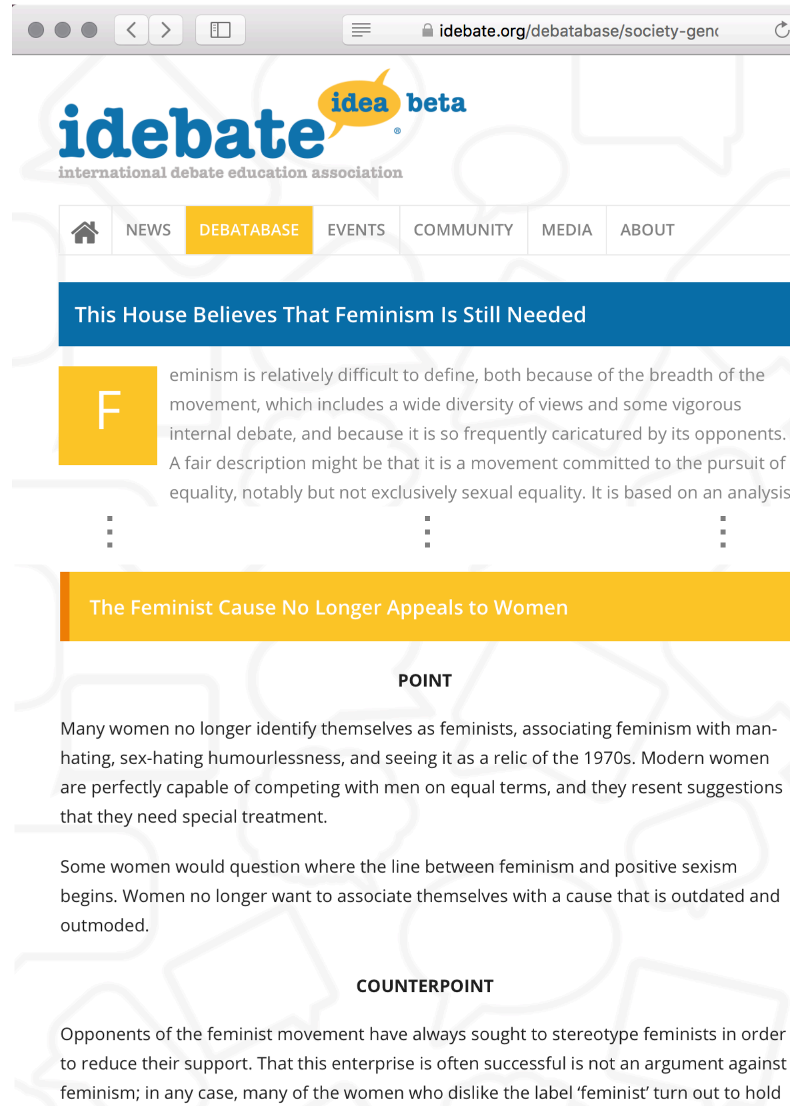
  - Argument ”wikis“. Each ”debate“ collects arguments on an issue.
    Examples: idebate.org, debatepedia.org, debatewise.org, kialo.com, procon.org,

https://commons.wikimedia.org

- **Information found in debate portals**
  - In nearly all. Pro and con stance of arguments.
  - In most. An introductory text each issue.
  - In several. Literature or web source of the arguments.
  - In some. Meta-information on the authors of arguments.
  - In some. User votings on arguments or stances.

Example debate portal: iDebate

- **Web portal iDebate.org**
  - ”Debates“ on controversial issues.
    e.g., Feminism is still needed
  - Categorized into 15 themes.
    economy, religion, society, ...
- **Arguments on the portal**
  - Up to six pro and con points on each issues.
    Each with conclusion and premise.
  - Collected by a community and revised multiple times.
  - A counterpoint to every point is given.
- **Size of iDebate (in January 2018)**
  - 1069 debates.
  - 6753 point-counterpoint pairs.



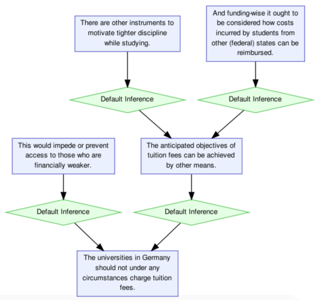
screenshots from https://idebate.org

Argumentation-related projects

- **ArguAna** www.arguana.com
  - Corpora, Java code, and tools for argumentation research.
- **Argument Web** www.argumentinterchange.org
  - Tools to create, analyze, and interact with arguments.
- **RATIO** www.spp-ratio.de
  - Priority program of the German research foundation with several projects.
- **UKP Argumentation mining** ukp.tu-darmstadt.de
  - Corpora, Java code, tools, and another argument search engine.
- **VisArgue** visargue.inf.uni-konstanz.de
  - Tools to visualize dialogical argumentation, with built-in text analyses.
- **And many more...**
  - rbutr.com, www.rationaleonline.com, cohere.open.ac.uk, www.archelogos.com, debategraph.org, www.argunet.org, evidence-hub.net, argumentz.com, www.truthmapping.com, https://diggingintodata.org, ...

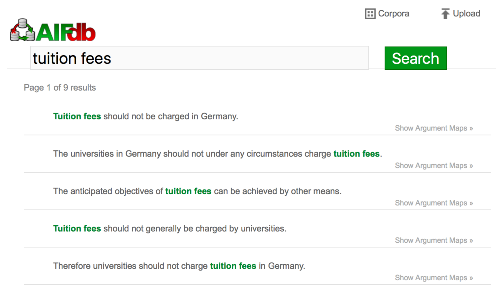
Example project: Argument Web

AIFdb Corpora



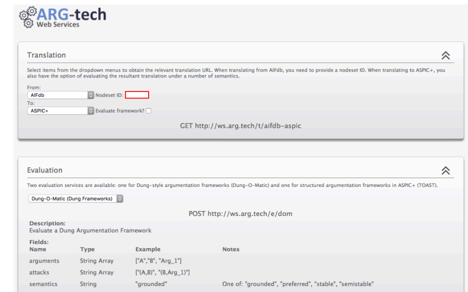
Structured argument data in uniform format

AIFdb Browser



Search interface for argument resources

ARG-tech API

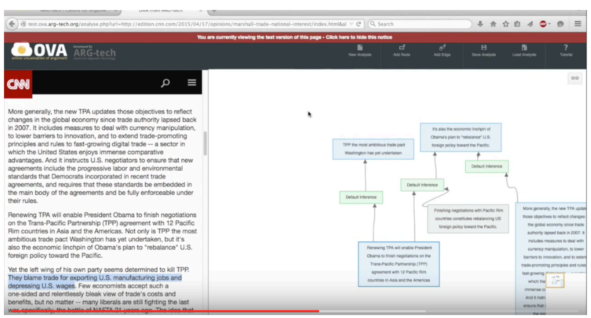


Several argument web services

Argublogging

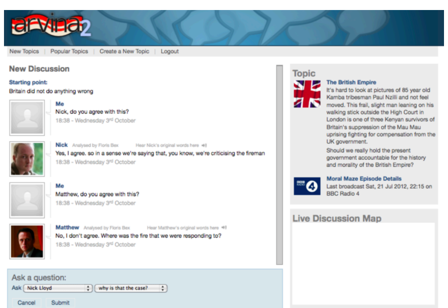
Widget for argument annotation in blogs

OVA



Online visualization and analysis of arguments

Arvina



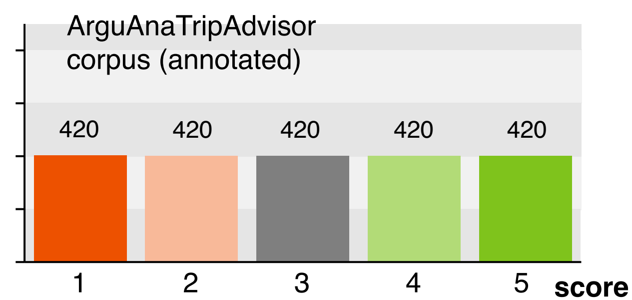
Dialog platform based on AIFdb

Conclusion

Conclusion

- **Resources for computational argumentation**
  - Text corpora annotated for arguments, stance, quality, ...
  - Focused lexicons, embedding models, and similar (still rare).
  - Web resources, code libraries, and tools.

- **Corpus creation**
  - Compilation of texts suitable to study a task.
  - Preprocessing and annotation of the input texts.
  - Analysis and postprocessing of annotated texts.



- **Important resources**
  - Particularly, corpora with argument structure are often used.
  - Debate portals are a rich source of argumentation.
  - No standard software, but some libraries and tools exist.

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