

Exploring a new approach for improving

# Argumentation Mining

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B.Tech. Project

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# Brief Introduction

## What is Argumentation Mining?

- **Argument:** conclusions can be reached through logical reasoning; that is, claims based, soundly or not, on premises.<sup>as defined by Wikipedia</sup>
- **Aim of Argumentation Mining:** automatically detect, classify and structure argumentation in text.<sup>[1]</sup>
  1. **Detect:** Separating out useless data, i.e. Non-Argumentative Text
  2. **Classify:** Classification into **Premises** and **Conclusions**.
  3. **Structure:** Finding out the structure of an argument and how different arguments are connected.

# State of the art

## Detection

- Similar to the **binary classification** of all the propositions of the text as **argumentative** or **non-argumentative**.
- **Limitation:** Requires text *segmentation* beforehand, i.e. we must figure out how information is split while forming individual arguments.
- State of the art [1]:
  - Classifier: **Maximum Entropy Model**
  - Features Used:
    - Unigrams, Bigrams, Trigrams, Adverbs, Verbs, Word Couples, Text Statistics, Punctuations, Keywords, Modal auxiliary, Parse Features
  - Accuracy:
    - **73% - 80%**

# State of the art

# Classification

- Again, **binary classification** of all the *argumentative propositions* as **premises** or **conclusions**.
- State of the art [1]:
  - Classifier: **SVM**
  - Features Used:
    - More Sophisticated This Time.
    - Absolute Location, Sentence Length, Tense of Main Verb, History, Rhetorical Patterns, Article Reference, Argumentative Patterns, Type of Subject, Type of Main Verb.
  - Accuracy:
    - **68% - 74%**

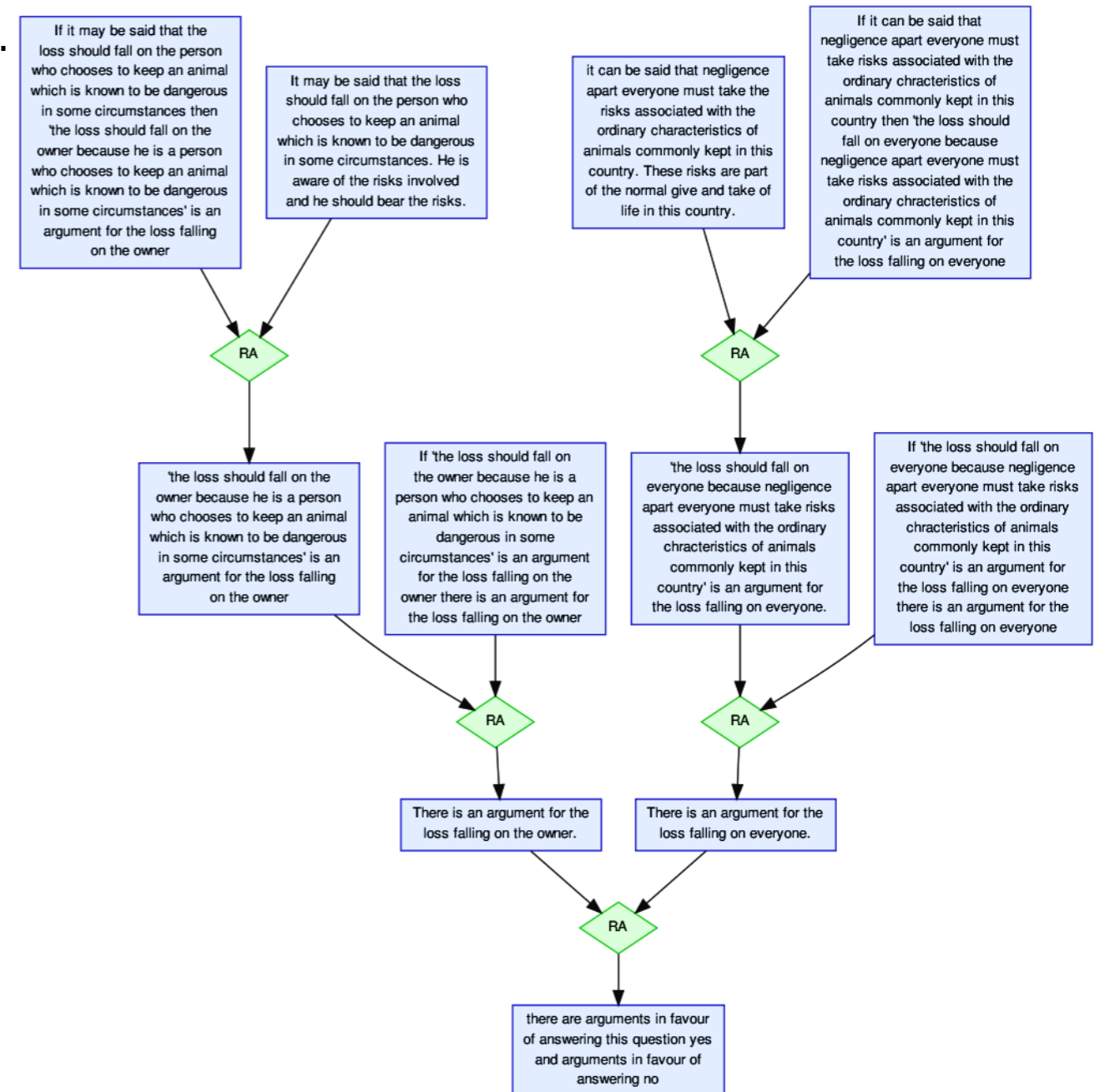
# State of the art

## Structure

- Undoubtedly, The hardest task.
- State of the art?
  - None really.
  - [1] uses CFGs to generate argumentative structures.
  - **Approaches towards automated mining:**
    - [3] Joining propositions with euclidean distance (over LDA modelled topics) below a threshold, Accuracy : **33%** - **60%**. Also the joining in this work is bidirectional, hence no information of conclusions is obtained.

# The General Structure of an Argument

- Can be represented in many cases as a tree.
- Assumption supported by around **95%** of argument analyses of AIFDb [3]
- [1] claims that an individual argument can be identified by its unique corresponding conclusion.
- A conclusion can then form a support for another argument.
- Other Theories Include e.g.: (Freeman's Theory) Argumentative conversation between proponent and opponent, thus text contains **proponent nodes** and **opponent nodes**



# Our Proposed Problem

- Automatically structuring the arguments ***given*** the detected argumentative propositions (detection phase).
- ***Initial Approach:*** Formulating the problem as an **Optimization problem**, which will give rise to the *best argumentation scheme*.
- Upto date no work has been done which treats argumentation as an optimization problem. This is because quantifying the quality of an argumentation scheme is not an easy task.

# Going a little more explicit.

- **Input:** The set of argumentative propositions. Ordering information might as well turn out to be useful.
- **Output:** Directed edges between the input propositions describing the support relations. These edges can be *intra-argument* (**premise -> conclusion**) or *inter-argument* (**conclusion->conclusion** or **conclusion->premise**).
- **Accuracy:** Recall and Precision values corresponding to the manually annotated edges in the dataset.



# Formulating the Cost Function

- The entailment score of (premise, conclusion) pairs have should correspond to a better structure.
- Since arguments quite often form a recursive structure, premises can also entail premises, we have to come up with a measure when to break arguments. This can be taken into account using a threshold value for connecting propositions inside a argument inspired by [3].
- [4] Already uses textual entailment as the first stage of joining arguments and then uses argumentation theory to reject invalid arguments.
  - However the confidence level might not be above the threshold when individually annotating pairs, rather it should optimize the overall cost function.

# Textual Entailment System

- There are various existing systems for recognizing textual entailment (RTE problem) in a T-H (Text-Hypothesis) pair.
- Excitement Open Platform (EOP) is a generic architecture and a comprehensive implementation for textual inference in multiple languages. The platform includes state-of-art algorithms. It also provides APIs that can be trained on a resource and can be used for annotation. We implemented it and it worked okay.
- However, when it comes to argumentation, the entailment is much more complex. E.g. there can be various possible types of entailments:
  - Cause to effect, Practical Reasoning, Entailment by example, Expert Opinion, etc.
  - E.g.:
    - **Text:** Research shows that drivers speaking on a mobile phone have much slower reactions in braking tests than non-users, and are worse even than if they have been drinking.
    - **Hypothesis:** The use of cell-phones while driving is a public hazard.
    - Even the most advanced entailment systems couldn't annotate this as an entailment relation with appropriate confidence. EDITS (used by [4]) annotated this as NonEntailment with confidence 0.33.

# References

- [1]** Argumentation Mining, Moens et al., 2011
- [2]** Aifdb: Infrastructure for the argument web, Lawrence et al., 2012
- [3]** Mining Arguments From 19th Century Philosophical Texts Using Topic Based Modelling, Lawrence et al., 2014
- [4]** Combining Textual Entailment and Argumentation Theory for Supporting Online Debates Interactions, Cabrio et al., 2012