A Persuasive Chatbot using a Crowd-Sourced Argument Graph and Concerns

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Intro - Chatbots

- **Chatbots** are software systems that can converse with people via speech or text (text in our setting)
- They are versatile tools with potential of being used as agents in **dialogical argumentation systems** (e.g. in behaviour change applications)

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- Example: chatbot (persuader) persuades people (persuadee) to do more sports

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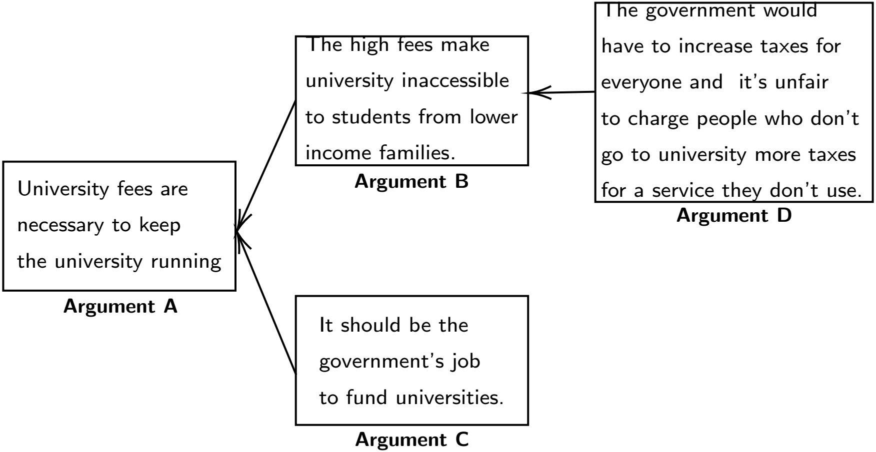
- **Argument graphs** are extensively studied in the computational argumentation literature
- Acquisition tends to be neglected and most papers have made up examples
- Availability of large argument graphs for research very limited

Example of Chatbot Knowledge as Argument Graph

Figure 1: Simple argument graph with arguments B and C attacking argument A and argument D attacking argument B.



Previous work

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- Dialogue consisted of argument-counterargument pairs
- Aim of this paper: Develop Chatbot that can understand user arguments and provide counterarguments to the user's arguments (given in free text input) instead of just listing all arguments in the repository

Argument-Counterargument

However, eating less meat will have a positive effect upon the environment, helping to slow down the rapid rates of deforestation

I disagree

Why?

I think deforestation will happen anyway with growing businesses and building roads etc of our modern world

Ok, I see.

However, eating less meat improves your general health, enables your digestive system to process foods more easily and gives you more energy, leaving you feeling less sluggish and tired

Argument Acquisition

- Important that the argument graph has sufficient depth and breadth of coverage of the topic
- Depending on topic, acquisition might be problematic
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- Current techniques include manual argument extraction and argument mining
- We have presented another possible method of acquiring such a graph in a previous paper[1] by using **crowd sourcing**

[1] Knowledge Acquisition and Corpus for Argumentation-Based Chatbots

Existing Approaches of Chatbot Knowledge Generation

Example	Chatbot	Automated	Graph-Form
Default Chatbot KB	✓		
Huang et al[2]	✓	✓	
Debating sites (e.g. Toniuc, Groza[3])	✓	(✓)	?
Hunter, Hadoux[4]	✓		✓
D-BAS[5]		(✓)	✓
IBM Debater[6]	✓	✓	

[2] *Extracting Chatbot Knowledge from Online Discussion Forums*

[3] *Climebot: An Argumentative Agent for Climate Change*

[4] *Comfort or Safety? Gathering and Using the Concerns of a Participant for Better Persuasion*

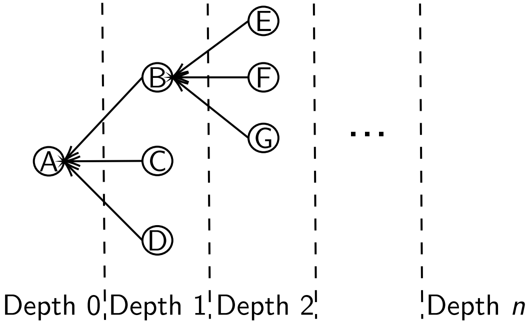
[5] *D-BAS - A dialog-based online argumentation system*

[6] *Towards an argumentative content search engine using weak supervision*

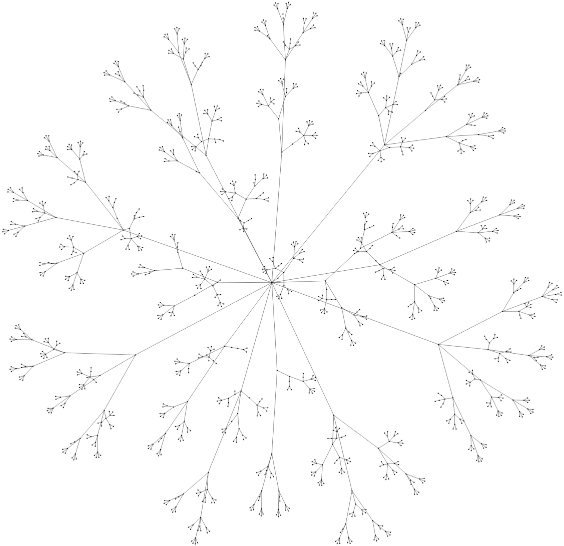
Our Argument Graph

- University Fees in UK as case study
- Created graph with 5 levels of depth with average of 3 counterarguments
- Depth: Max number of arcs to follow starting from root
- Arguments in depth 2 are attacking arguments in depth 1 etc.

Figure 2: Representation of depths and attack relationships between arguments in our argument graph. Arguments *B*, *C* and *D* are counterarguments to *A*.



Corpus with 1288 arguments



Hypotheses

1. A crowd-sourced argument graph can be used as a knowledge base for a persuasive chatbot allowing free text input by the users. The resulting chats are of appropriate length and quality, and the chatbot arguments perceived as relevant by the users
2. A concern raised or addressed by a given user argument can be automatically identified in order to give appropriate counterarguments that address the same concern and thereby increase the persuasiveness of the dialogue.

Chatbot Design - Argument Graph

- Chatbot utilised depths 1-4 of the argument graph as a knowledge base
- Created a baseline and a strategic chatbot. Baseline did not take the concern of the user into account while the strategic one did

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- User typed in an argument (source argument) in free form and the chatbot used cosine similarity to find the closest match of the user argument in the graph (target argument)
- If the chatbot found a target argument in the graph it chose one of the counterarguments that attack the target argument in the graph as its response

Chatbot Design - Default Arguments

- In case no target argument was found, we also acquired arguments for keeping university fees
- We again used crowd-sourcing for the acquisition and voting in order to select the best arguments
- The best 7 arguments were used as default arguments, which the chatbot could use if no match was found

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- During the acquisition of the argument graph only arguments that contained topic words were included. common words that we considered meaningful in the given context
- We grouped topic words that address the same or similar issues into 5 concerns: **Student Finance** (loan, debt, scholarship, interest), **Government Finance** (government, tax), **Employment** (job, career), **Free Education** (free) and **Fairness** (affordable, accessible, background).

Chatbot Design - Concern Classification

- We used the arguments from the argument graph, as well as the user arguments from the chats with the baseline chatbot that contained any of the topic words, to train a concern classifier
- The strategic chatbot used the classifier to predict the concern of the user argument

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- The strategic chatbot used the classifier to predict the concern of the user argument
- If a target argument in the graph was found, the chatbot chose one of the attackers that addressed the same concern as counterargument
- If no match in the graph was found or none of the counterarguments of the target argument addressed the same concern, the chatbot replied with a default argument

Evaluation

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- Before the chat the users were directed to a Google Form and asked whether they *strongly disagreed,disagreed*, *neutral*, *agreed* or *strongly agreed* that university fees should be kept
- At the end of the chat the chatbot presented the user with a link that redirected them to a second Google Form where they were asked a series of questions
  1. Did you feel understood by the chatbot? (Yes/No/Sometimes)
  2. Did you feel that the chatbot's arguments were relevant? (Yes/No/Sometimes)
  3. Do you feel like all your points were addressed? (Yes/No/Some of them)
  4. How much do you agree that fees in the UK should be kept as they are? (Strongly disagree - strongly agree

Evaluation

Questions 1-3 were used to test our first hypothesis and judge the relevance, length and quality of the chats

Table 1: Answers to first three questions for baseline and strategic groups

Chatbot	Understood (Q1)			Relevant Args (Q2)			Points addresses (Q3)		
	Yes	No	Sometimes	Yes	No	Some	Yes	No	Some
Baseline	16	4	30	21	3	26	13	15	22
Strategic	15	6	29	31	1	18	10	14	26

Evaluation

- There is a 50% increase in the perception of relevance for the strategic chatbot, while the numbers for questions 1 and 3 remained almost the same
- This is a statistically significant difference with a p-value of 0.045 using Chi-Square
- On average chats lasted 24 turns, meaning that the chatbot gave 12 arguments (7 default arguments and 5 from the graph)

This supports our first hypothesis that a crowd-sourced argument graph can be used as a chatbot knowledge base and that the resulting argumentation dialogues are of satisfactory length and quality, with perceived relevance of the arguments being 50% higher during chats with the strategic chatbot

Evaluation

- Question 4 was used to test our second hypothesis and compare the persuasiveness of the baseline chatbot to the strategic chatbot
- Used replies for Q4 to calculate the change in stance for both groups
- The change in stance is the final stance (after the chat) minus the original stance (before the chat). We call the units of this measure change in stance (CS) points
- Example: Changing stance from *disagree* to *neutral* is $+1$ CS

Evaluation

The table shows the number of participants who changed their stance to the worse (negative), to the better (positive), and that did not change their stance at all (no change) for both chatbots, as well as the number of total CS points.

Table 2: Change of stance measured by number of participants and CS points

Chatbot	Baseline			Strategic		
Change in stance	Neg.	No Change	Pos.	Neg.	No Change	Pos.
No. of participants	5	41	4	1	26	23
Change in CS points	-5	0	5	-1	0	32

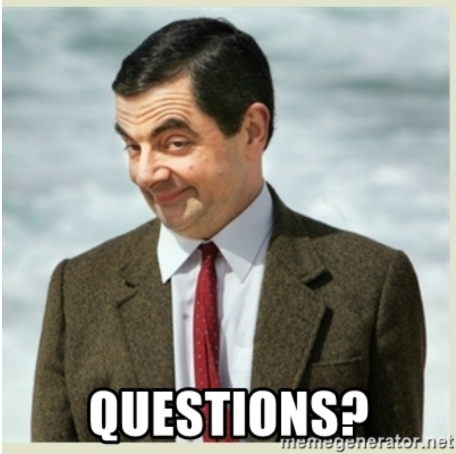
Evaluation

- The strategic chatbot achieved a total change of 31 CS points whereas for the baseline the total number of CS points is 0
- We used the number of participants who changed their stance to the positive in order to calculate the statistical significance of the difference between the baseline chatbot and the strategic chatbot using the Chi-Square test
- All results were statistically significant with a p-value of 0.00017

The results support our second hypothesis, that concerns can be automatically classified based on the use of topic key words and that presenting arguments that address the user's concern is more likely to have a positive impact on their stance, than presenting arguments that ignore the user's concern

Contributions

- We have shown that a crowdsourced argument graph can be utilised as a knowledge base for a chatbot that engages in argumentative dialogues
- And that concerns can be automatically identified in order to give suitable counterarguments that address the same concern and thereby significantly increase the persuasiveness of the dialogue.
- Additionally, we have shown that the chatbot can jump around in the graph, without systematically following each arc and only use arguments that are connected via an attack relationship


QUESTIONS?
memegenerator.net

Freedom for Belarus

I would like to raise awareness to the current situation in Belarus. If you would like to help, feel free to reach out to me and I can direct you to legit, tested fundraisers. (Alternatively, you can contribute locally by helping families in need. Knowing Russian helps but I can help!)