Introduction

The purpose of this agent was to take in a syllabus of statements, learn from these statements, and provide answers to yes-no-idk questions. In this discussion, we will follow the agent through the steps of reading statements, constructing concepts, and answering questions.

Building the Syllabus

(1) The final must be submitted to piazza

The syllabus is given to the agent as a list of statements, like the one above. Our agent must read these statements, then interpret their meaning and relation to a select group of concepts that may be in the syllabus. Our agent has a limited vocabulary and a limited domain of concepts that can be described. These restrictions define our agents Grammar. Like a human, our agent uses basic grammar rules to find the basic structure of the sentence. What is the subject of the sentence? Is there a verb? Is the subject performing that action on to another object? By programming rules around these types of questions we can allow our agent to think like us. Our agent attempts to emulate human-cognition. Given a list of sentences, how would you go about learning them?

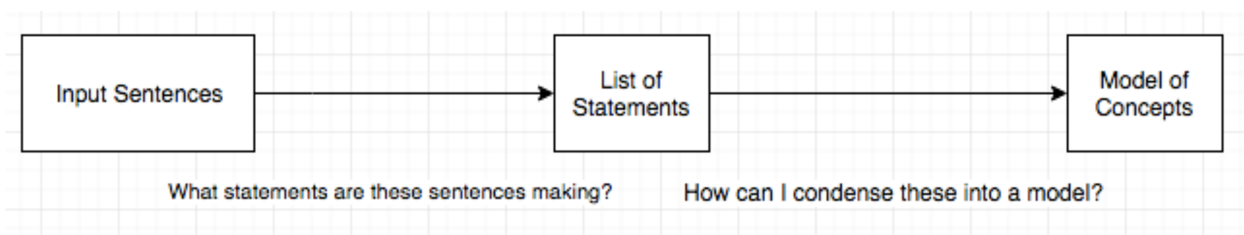

Figure 1: Human approach to Building a Syllabus

Not only does our agent utilize parts of speech and sentence structure, it also can recognize key words that strongly point towards certain concepts or relationships. For example, submission-style concepts like assignments, reports, projects, midterm, and final will commonly have attributes like a release date, due date, or process. Our agent uses this domain knowledge to understand important aspects of a concept. Below, I diagram the way a human would go about breaking down and understanding statement (1).

Upon first reading the sentence, the human mind wants to address who or what is being talked about. In our world, we have 24 topics that may be described. Among them is the final. Our agent identifies the one and only concept in the subject. Next, we must see what the subject is doing; or what is being described about the subject. We think of our vocabulary and grammar rules. “Must be [action]” is a common verb phrase. We recognize not only is this going to be how to submit the final, but also it is the only way. Now that we have deduced our subject and the attribute of the subject being described, we can learn the specifics. In the predicate, prepositional phrases will help us find direct objects, which we know modify how the final must be submitted: “to piazza.”

In the full syllabus, there are many statements. This agent was trained off of 27 statements. Some of these statements will describe the same thing. So how will we address this?

While each sentence is interpreted into a statement, we must have a way of keeping track of multiple statements describing the same idea. This is where we need concepts. A human knows an assignment will probably have a release date, a due date, and several processes associated with it. Our agent will use concepts to coalesce the many statements in to just a few concepts. General concepts, like the plural “projects,” will need fewer attributes, but may have multiple attributes that fill the same slot. For example, our syllabus may say that assignments may be turned into piazza or canvas. Specific concepts, like “assignment 1” will have very specific attributes. Assignment 1 can only have 1 due date. Common sense logic and case-based reasoning such as this is how a human absorbs, learns, and condenses information, and the agent seeks to take advantage of these techniques.

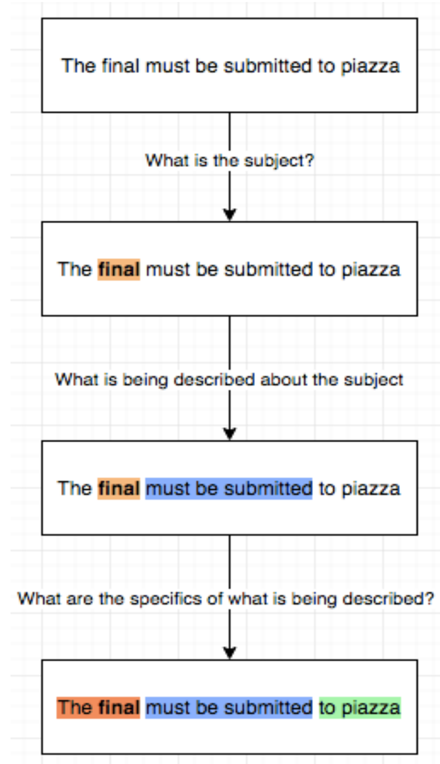

Figure 2: Human Approach to Decoding Sentences

However, humans and robots can suffer from similar cognitive issues as well. As we are given more and more information, it becomes harder to maintain it accurately and recall it quickly. As more and more statements are added to our syllabus, our agent will have a harder time deducing the most relevant information.

In our agent, our model is a list of concepts with relevant attributes. At the end of the process of condensing the interpreted statements, our model might contain a concept like below. In our syllabus, Project 1 has a due date during week 6, a release date during week 3, and is weighted at 10% of our grade.

```
Concept: project
Number: 1
Due Date: [['of', 'week', '6']]
Process: []
Release Date: [['of', 'week', '3']]
Weight: [['10%', 'of', 'the', 'grade']]
Duration: []
Modifiers: []
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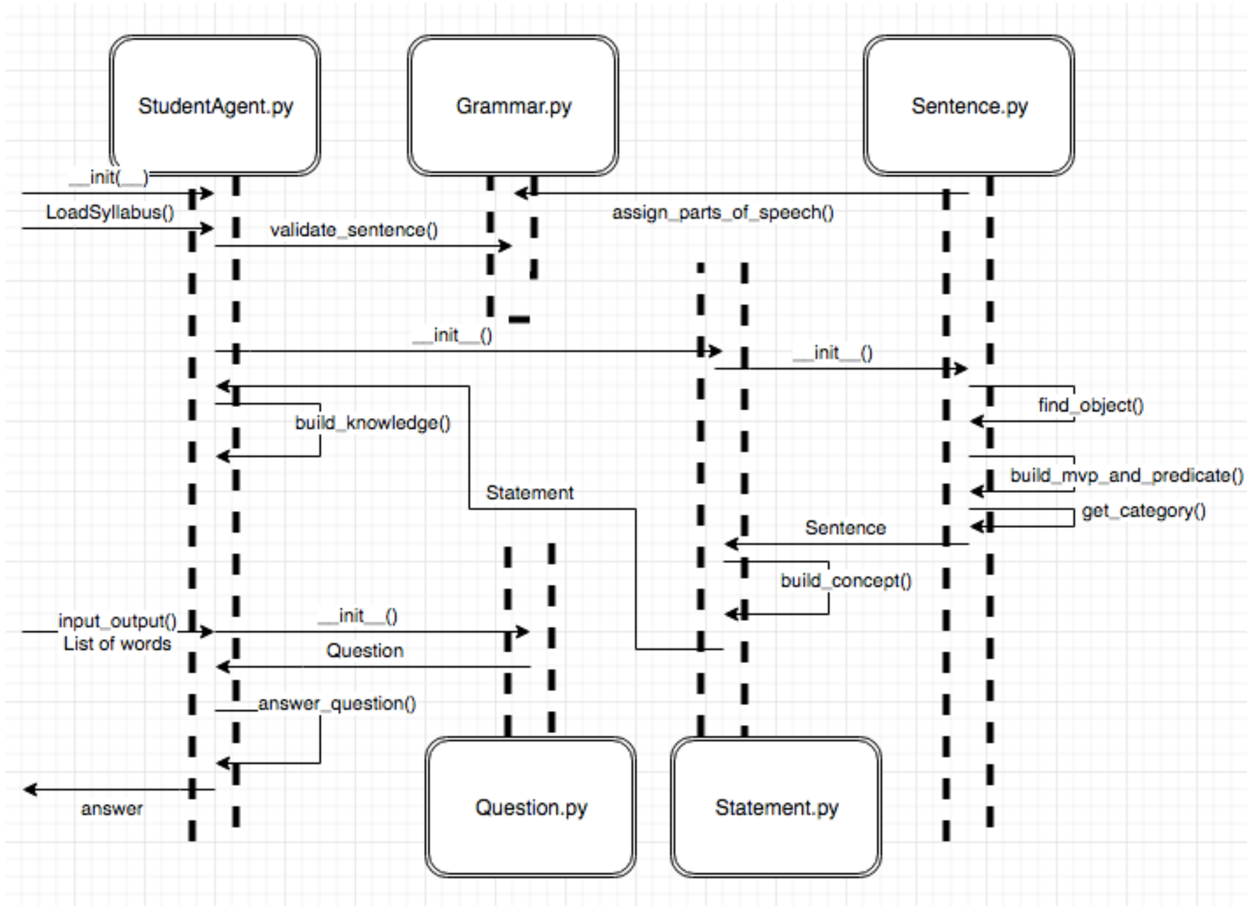

Figure 3: Agent Diagram

Details of Implementation

Pictured above is our agent. At the outset, the StudentAgent is initialized. Our agent keeps a list of statements interpreted and a knowledge-base of concepts. First, our agent will load the syllabus. For each statement provided, the agent first validates that it follows this project's specifications. The agent then calls to build a Statement from the words read in. A Statement is an object with a concept, a category or attribute, and a sentence.

The Statement begins building by first initializing a Sentence object. Here, the Sentence object takes in a list of words and begins decoding it. The parts of speech of the words are determined. Then, with this grammatical knowledge and case-based reasoning, our agent finds the object or concept of the sentence. The action being taken by or on the subject is then deduced. And finally, the attribute being described is discovered. This information is then returned to the Statement.

The Statement can now build a concept object that the statement has described from the information gleaned in the Sentence. Concept objects have a name as well as many modifiers. The Statement and corresponding Concept are returned to the StudentAgent.

After the agent's initial pass of the syllabus, it has created many Concepts with only one or two attributes. Now, our agent passes through all of these concepts, coalescing information where possible. The model of our agent has now been set and is ready to take questions.

At this point, the StudentAgent is posed a series of questions. Each question is parsed similarly to the sentences. There is a separate Question object that is tuned better for the questions present in this project. The Question object has a concept being asked about, an attribute being asked for, and a verb phrase that assists in checking nuances in yes-no-idk answers. The Question is returned to the agent. Here the agent is prepared to access its knowledge base, searching for the required concept or concepts, then making a detailed comparison to ensure accuracy in its answer. If the agent does not recognize a concept at all, it will respond "idk." If the agent recognizes the concept, but the attribute requested does not exist or the information in the question is incorrect, the agent will answer "no." Finally, if the concept is recognized, the attribute found, and details sorted, the agent will respond "yes."

Reflection and Relating to Human Cognition

While much simpler, the diagram at the beginning of this discussion is clearly a big-picture look at how our agent interacts with reading and absorbing the syllabus. For each statement, our agent uses grammatical rules to find important structural areas of the statement. It identifies the subject, attributes of the subject, and the details of these attributes. It then creates a series of concepts and condenses information about these concepts into a knowledge-base.

However, despite the overwhelming similarities, there are stark differences as well. Case-based reasoning in an AI is sometimes overwhelming. Long-winded if-statements and complicated programming is required. Generalization is difficult, as there are many cases to be represented and often-times there are many edge-cases that can throw a wrench in your model.

With 24 different describable topics there is a lot of room for specialization, while there is plenty of opportunity for generalization. This is a fundamental trade-off in knowledge-based AI. With more specialization, accuracy can be improved, the domain of the agent can be improved with expert-level knowledge. However, with more generalization, a wider domain can be tackled but the accuracy is more difficult to achieve. Generalizing the decomposition of sentences unfortunately weakens the agent's resistance to edge-cases. This agent only performs a somewhat basic analysis of the sentence parts of speech and underlying structure. Once the important words have been discovered, case-based reasoning on what the agent should do takes over.

Humans are much more capable of learning in that they can perform garbage collection, filter out bad information, and react to new experiences much faster. We can realize information being fed to us is bad, much in the same way an agent could, but an agent would be much slower and more prone to making mistakes.

Humans and agents will also behave similarly as the quantity of information is increased. Agents will always have better, if not perfect, recall, but a human will be much better at combining previously gained knowledge to answer a question. Asking an agent "Is Assignment 1 due on week 3" is a simple query and comparison. However, asking an agent "Is the midterm after assignment 2" is more difficult. The agent needs to ensure it gets the correct attributes form the appropriate concepts and performs the correct arithmetic. Something a human is much more capable of.

With a limited vocabulary, it is only a matter of time and learning before the agent has learned the vast majority of possible questions and statements. However, as the vocabulary grows, the agent suffers. As more words are added, the possibility for words to be used with more than one meaning increases. Words may be repeated in a single sentence. If this vocabulary were to scale infinitely, the amount of code required to program it would be infinite as well. Humans are much more suited at the present moment for dealing with what often feels like the infinite vocabulary we use every day. We can make faster connections, keep track of more concepts, keep track of concurrent concepts, and learn with a single glance. And, we are born to do it. AI today is requiring too much programming to be as remarkable as a human. Some of the smartest AI agents like Wolfram-Alpha have had hundreds of thousands of man-hours spent on giving them a fraction of human intelligence. Be it a contest in recall, an agent will certainly win. Humans were born to learn, and we still do it better than machines.

Speculation

What makes a question-answer system robust? A robust answering system requires 100% accuracy with respect to the completeness of the knowledge base. In my mind, a more robust agent will have much fewer "idk" responses than yes or no's. At the same time, a robust agent needs to be aware of its own limitations. An accurate description of the vocabulary is needed. If the agent is not fully aware of the bounds of its grammar, it will be ineffective at reasoning with that grammar. Because of this, I believe that Ashok Goel is actually a knowledge-based AI agent. His answers on piazza are always correct. Only an KBAI agent could be that robust.

Over this course, the most difficult obstacle has been programming grammar rules and constraints. The English language is flexible and vast. To be able to understand it requires a deep knowledge of how that grammar works. Especially when attempting to generalize an agent. Because of this, I believe that Ashok Goel is actually a knowledge-based AI agent.

This agent's strengths include a flexible approach to recording modifiers with an unclear attribute. With 24 different possible concepts, many classes would be needed to describe each perfectly. The agent is also flexible in answering questions. If the agent cannot find the information it needs where it believes the question is asking, it will try to search all attributes. However, this opens the agent up to mistakes and misunderstandings. A million if statements cannot be written, so scoring schematics and keyword analysis is necessary to try to handle tie-breakers.

The agent's greatest weakness is inflexibility. Generalization was difficult and created more problems than it solved at times. Thus, the agent's model is extremely dependent on the variability and scope of the training data. If lots of complex training data is given with extremely similar concepts with multiple shared attributes, the agent will answer incorrectly more often. If the training data is kept focused and clear, the agent performs much better.

All in all, the agent attempts to make sense of a syllabus of statements, train a model based on inferences gained, and answer questions about the built model.