Big Data in Education

Assessment of the New Educational Standards

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Big Data in Education

"Technology is disrupting education, expanding the education ecosystem beyond traditional lecture halls and classrooms to accommodate learners' preferences for time, place, style and previous levels of attainment." [Gartner Technology Research, 2013]

Educational data is gathered through traditional assessments and increasingly also through educational games and simulations.
=> Lots of data!

New Standards in K-12 Education

The new Common Core State Standards (CCSS) in math and English language arts and the Next Generation Science Standards (NGSS) propose a shift from multiple-choice items towards short-answer response items or short essays.

Explanations, Argumentation, and Communication are central Science and Engineering Practices ("A framework for K-12 science education," National Research Council, 2012, http://www.nap.edu/openbook.php?record_id=13165)

Deep learning and application of knowledge, rather than memorization and rote learning are favored.

Consequences of New Standards

- The new standards require new assessment approaches.
- Tradeoff between problem realism and scoring difficulty: The more naturalistic the assessment item, the harder it is to score.
- Assessment of explanations, argumentation, and communication mostly require constructed responses (i.e. text)
- Approximately 25 million students will have to write at least two essays a year, not including the number of short answer constructed responses. [Bennett, 2013]
- Valid, informative, automated assessment scoring is needed.

Automated Scoring

- Machine scoring of constructed responses is generally not amenable to exact-matching approaches because the specific form(s) and/or content of the correct answer(s) is not known in advance.
- The state of the art of automated scoring depends highly on the domain that is scored.
- Some answer types that have been scored automatically to-date are essays, short-text, equations and expressions (math).
- We will focus on automated evaluation of text…

Why Automated Text Evaluation?

- To score student essays or short-answer responses.
- To understand textual information on the web, in books, or any other information resource.
- To organize information semantically so that it can easily be found and accessed.
- To make sense of Big Data.

Some Issues in Automated Essay Scoring

- Currently, automated essay scoring uses machine learning algorithms and models which are mainly trained on statistical text measures, such as word choice, text length, grammatical measures, and punctuation.

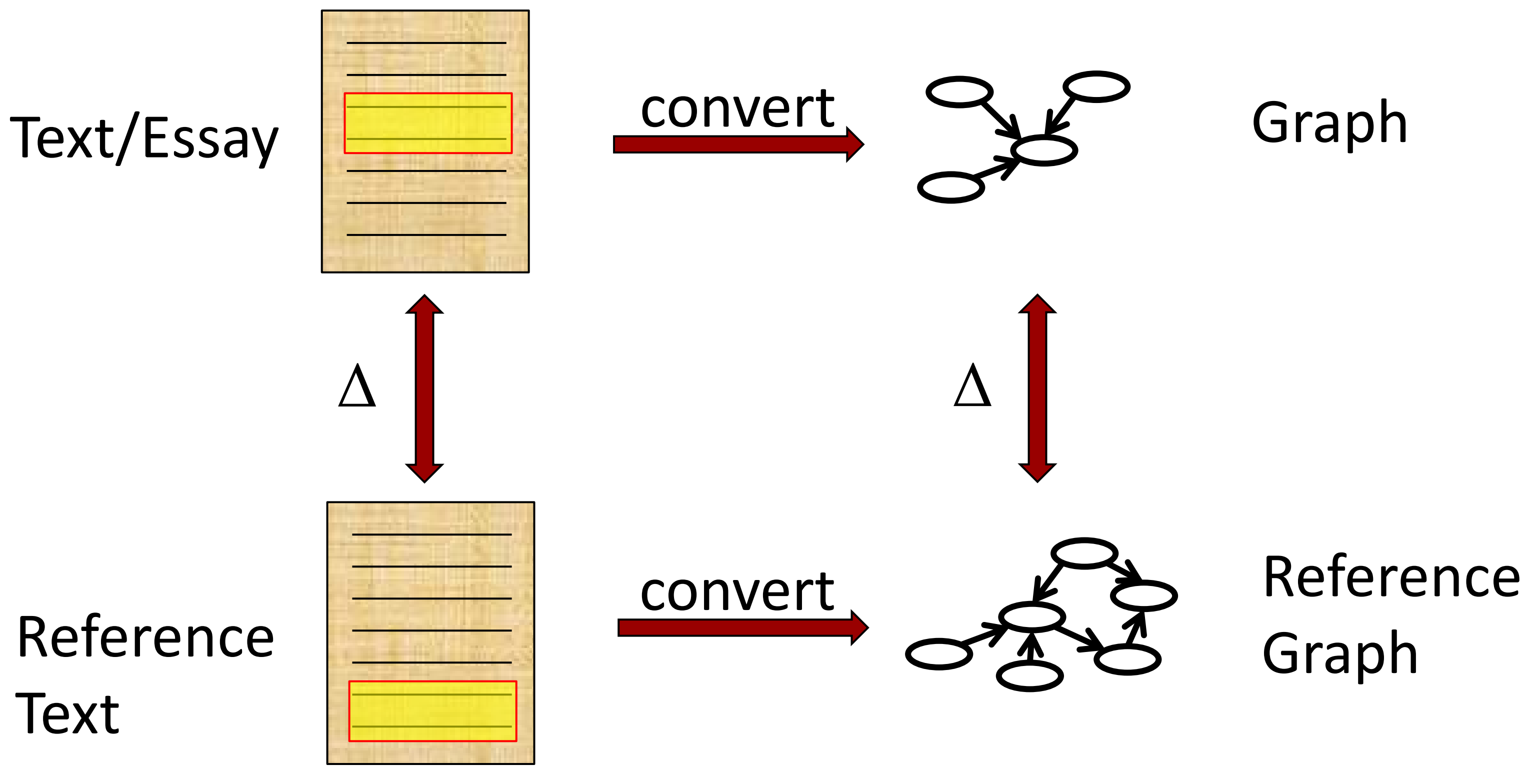
- The resulting models are not scalable, since they are highly domain/topic-dependent and require large amounts of human-scored essay data.

- The model outcomes are scores, numbers that are correlated with human rater scores but that contain no information about essay content and provide almost no clues on the underlying reasons of this number's value. (more diplomatic)

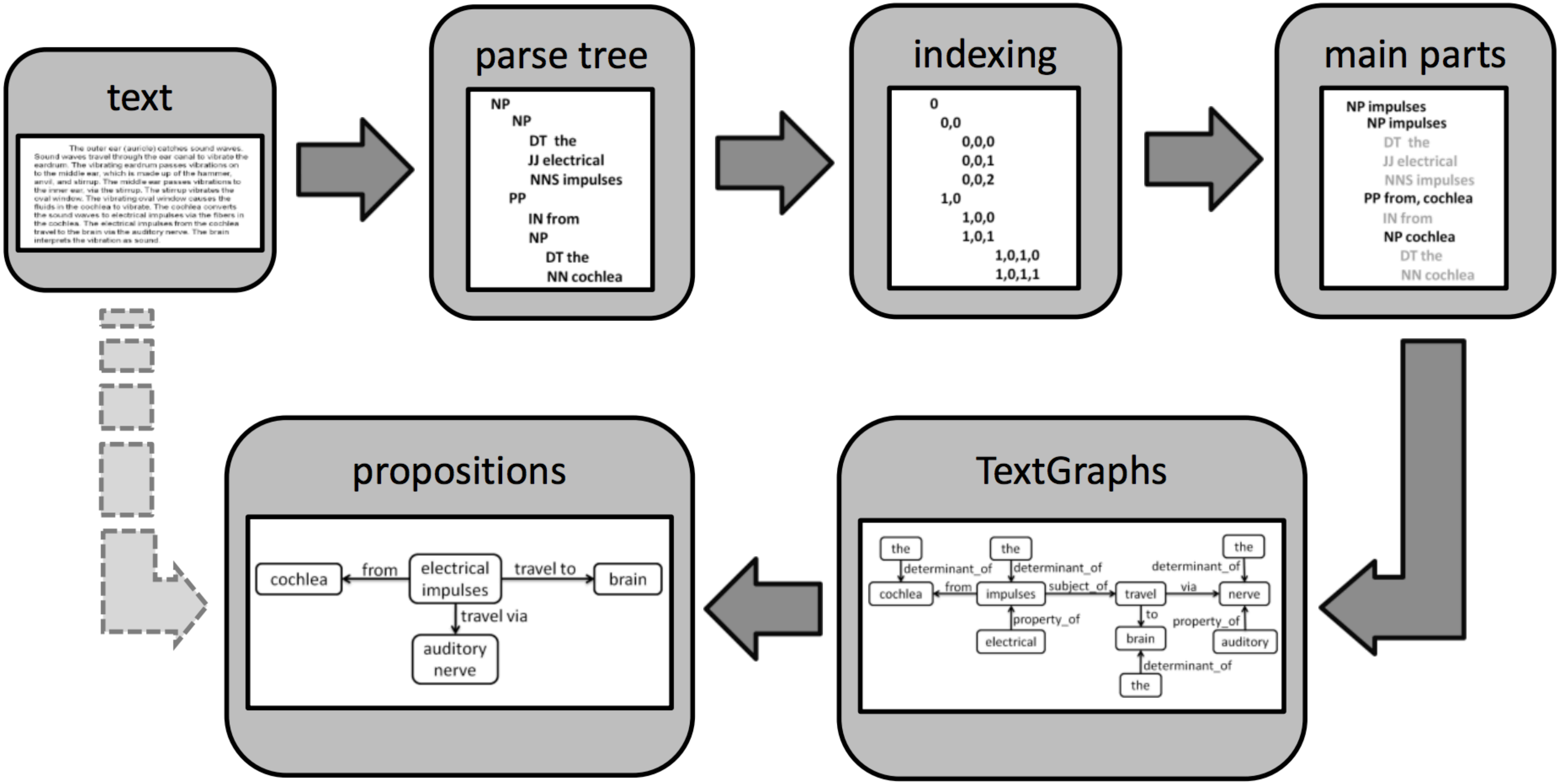
How We Addressed These Issues

- Focus on the evaluation of essay **content** and leave the evaluation of statistical text properties to other engines.
- Teach the computer how humans evaluate content: give it some rules and algorithms.
- Provide the computer with a reference text, which contains all the content that should be mentioned in the essay.
- These rules and algorithms can be applied to any other textual data. If scalable, even to Big Data.

Text to Graph



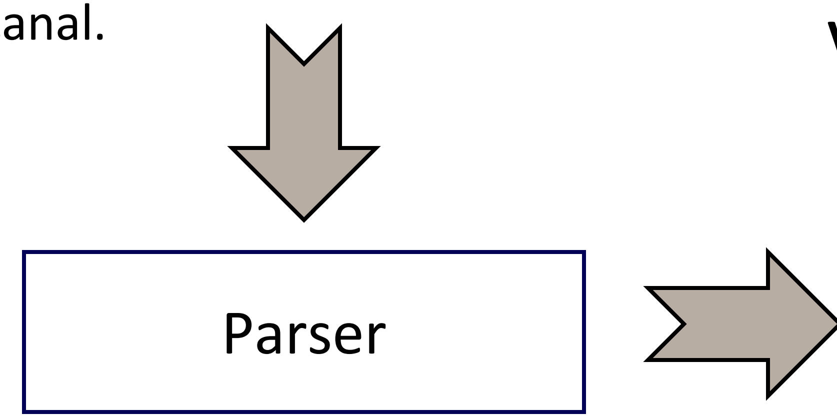
System Overview



National Center for Research on Evaluation, Standards, & Student Testing

How to Create Ontology: Parsing

The outer ear catches the sound waves and puts them through the ear canal.

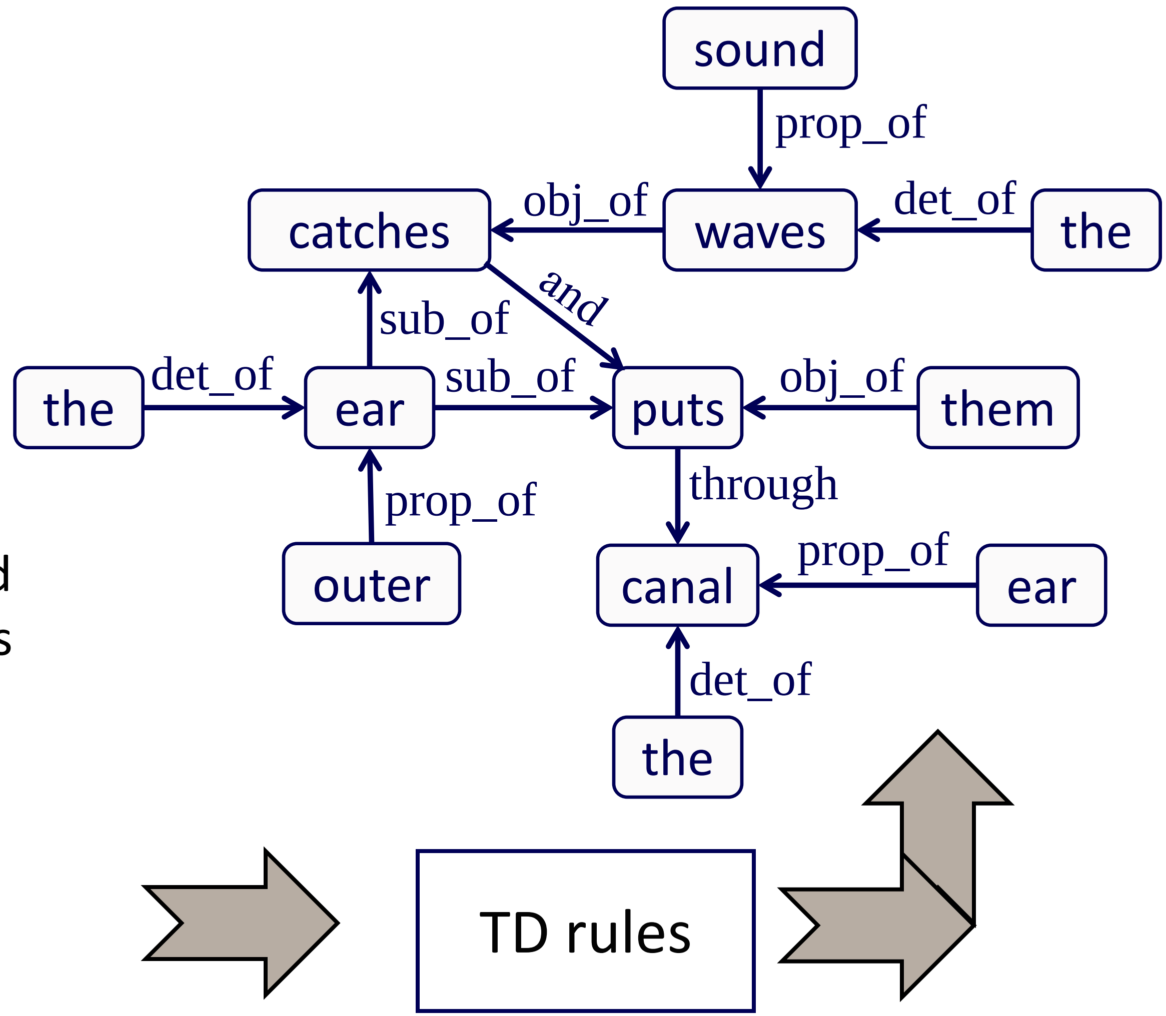



```
NP
    DT    the
    JJ    outer
    NN    ear
VP
    VBZ   catches
        NP
            DT    the
                NN    sound
                NNS   waves
    CC    and
    VBZ   puts
        NP
            PRP   them
```

etc.

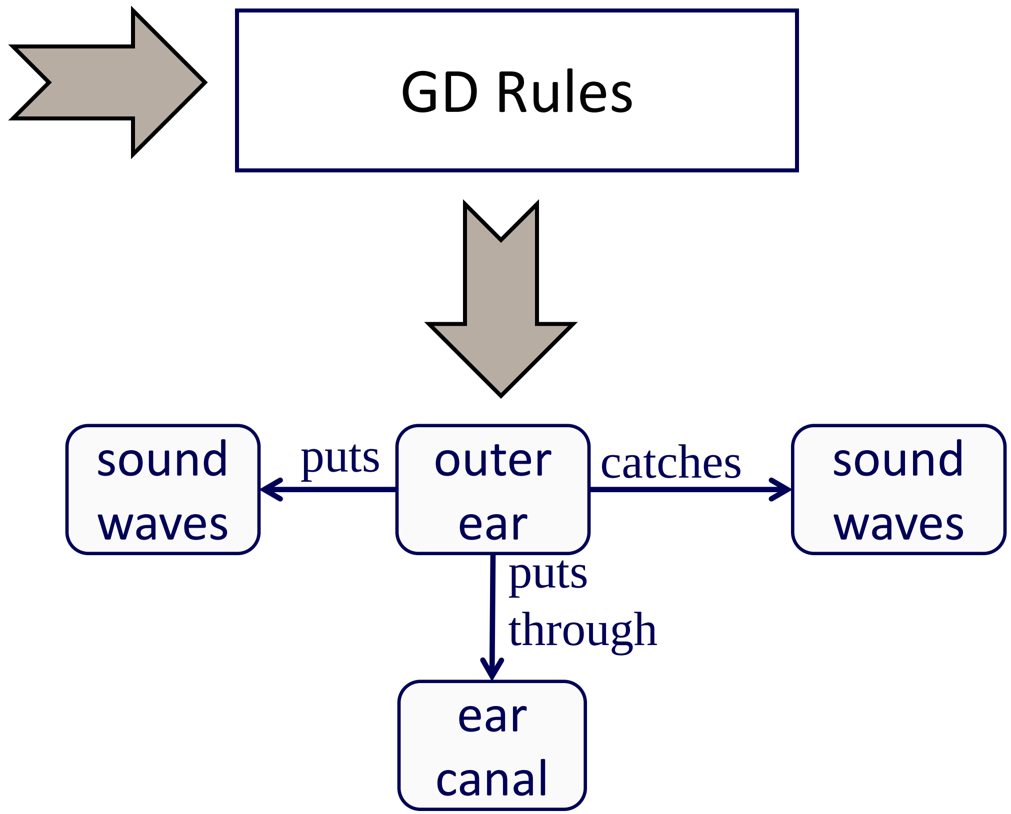
TextGraph

NP
DT the
JJ outer
NN ear
VP
VBZ catches
NP
DT the
NN sound
NNS waves
CC and
VBZ puts
NP
PRP them
etc.



Propositions

The outer ear catches the sound waves and puts them through the ear canal.



Essay Evaluation Study

- Write rules and algorithms to extract propositions
- Apply rules and algorithms to 55 short essays about the human hearing process (4th and 5th grade students)
- Apply *same* rules and algorithms to 54 short essays about the vision process (4th and 5th grade)
- Provide reference essays and scoring rubrics in terms of propositions for both topics
- Compare performance of our rules and algorithms for the two topics and compare to human analysis

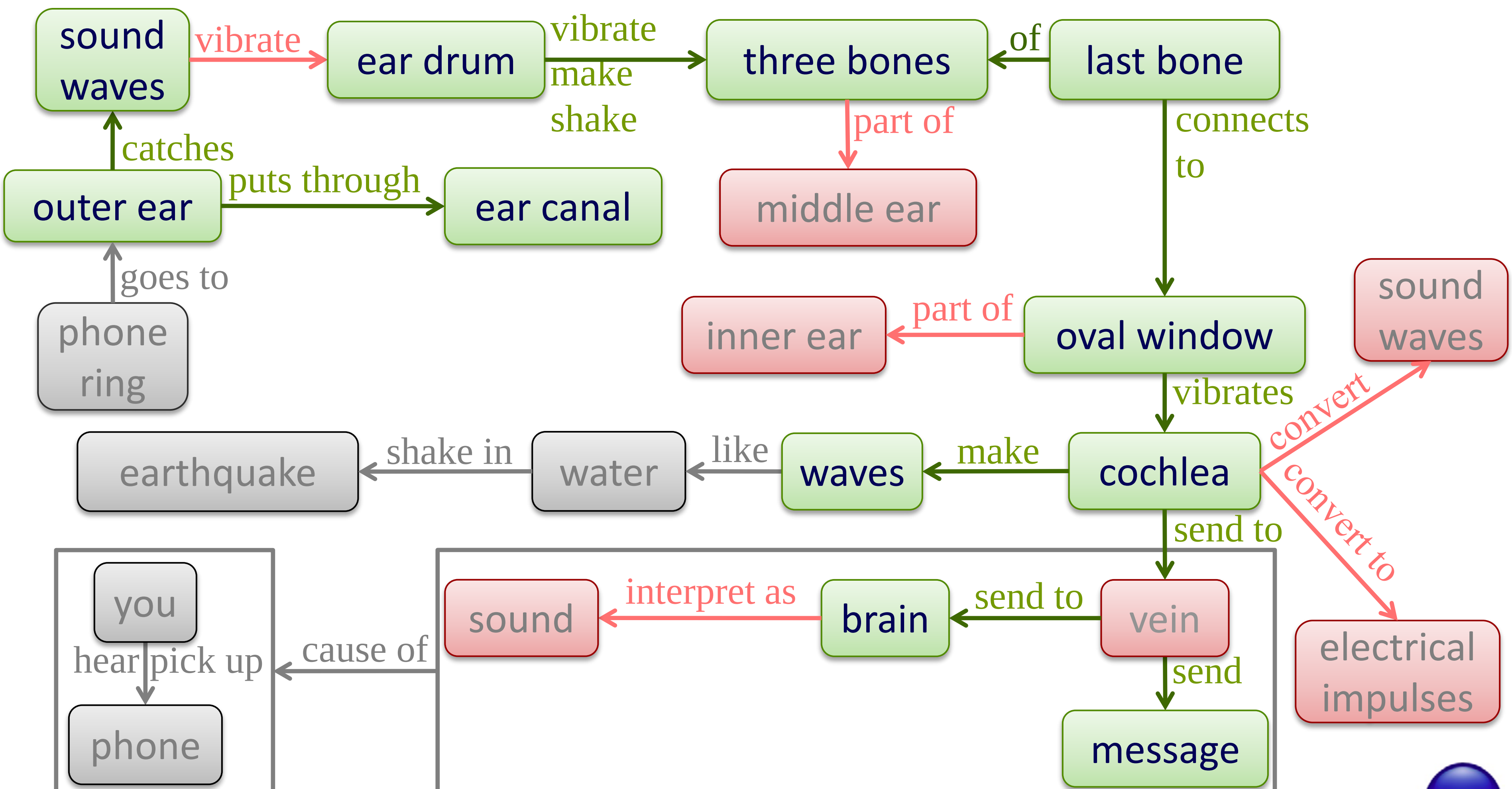
Hearing Process Reference Essay

The outer ear (auricle) catches sound waves. Sound waves travel through the ear canal to vibrate the eardrum. The vibrating eardrum passes vibrations on to the middle ear, which is made up of the hammer, anvil, and stirrup. The middle ear passes vibrations to the inner ear, via the stirrup. The stirrup vibrates the oval window. The vibrating oval window causes the fluids in the cochlea to vibrate. The cochlea converts the sound waves to electrical impulses via the fibers in the cochlea. The electrical impulses from the cochlea travel to the brain via the auditory nerve. The brain interprets the vibration as sound.

Hearing Processing Sample Essay

When the phone rings, it goes to the outer ear. The outer ear catches the sound waves and puts them through the ear canal. Then the eardrum vibrates and makes the three bones to shake. Then the last bone of the three bones connects to the oval window and the cochlea makes waves like water that shakes in an earthquake and it sends it to a vein. Then it sends the message to the brain and you will hear it and you will pick it up.

Proposition Comparison



Study Results in Terms of Scores

Comparison of SemScape to Human Raters for Hearing Essays

	SemScape score					
Human score	1	2	3	4	5	Percent matched
1	**1**	-	-	-	-	100%
2	-	**7**	3	-	-	70%
3	-	2	**6**	3	-	55%
4	-	-	8	**15**	2	60%
5	-	-	-	4	**4**	50%

r = .798, qwk = .792

Comparison of SemScape to Human Raters for Vision Essays

	SemScape score					
Human score	1	2	3	4	5	Percent matched
1	-	-	-	-	-	100%
2	-	**6**	4	1	1	50%
3	-	-	**8**	9	2	42%
4	-	-	1	**11**	6	61%
5	-	-	-	1	**4**	80%

r = .682, qwk = .6

Study Results in Terms of Propositions

- Proposition Extraction: avg. precision 79%, avg. recall 65%
- The 35% of propositions that were not successfully extracted were split between Wrong (20%) and Missing (15%) propositions.
- Wrong propositions were largely due to incorrect pronoun resolution
- Missing propositions were largely due to uncommon or inaccurate sentence structures for which there were no applicable TextGraph rules

Issues and Possible Improvements

- Parse tree generation: Only extract information needed
- Rule generation is language and language style dependent and is manual: Use automatic rule generation strategies
- Graph comparison: Simplify graph structure and split into subgraphs to compare more complex patterns
- Ambiguous statements will still be ambiguous
- World knowledge ontologies required

Take Away

- No human-scored training data is required, only reference text or reference propositions
- Once the rules are established, they don't need to be changed for different domains/topics since they are purely grammar-dependent
- Content analysis provides feedback on understanding and misconceptions
- Approach can be applied to Big Textual Data – once it has been engineered some more…
- http://www.cresst.org/products/reports/R836.pdf

Thank You!

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Text Domain (TD) Rules

```
NP
    DT    the
    JJ    outer
    NN    ear
VP
    VBZ   catches
        NP
            DT    the
                NN    sound
                NNS   waves
    CC    and
    VBZ   puts
        NP
            PRP   them
```

etc.

Given:		Output:
0	NP	<0,1 prop_of 0,2>
0,0	DT	
0,1	JJ|NN	
0,2	NN|NNS	

outer $\xrightarrow{\text{prop\_of}}$ ear

sound $\xrightarrow{\text{prop\_of}}$ waves

Graph Domain (GD) Rules

Given: <*a* sub_of *b*> and <*c* obj_of *b*>
Output: <*a*, *b*, *c*>