Graphing with Python
Textual Entailment

Methods in Computational Linguistic II

Today

Drawing graphs with Python

Plotting with NLTK

Recognizing Textual Entailment

Course Recap

Graphics in Python and NLTK

Through matplotlib, python has some very helpful graphics options.

NLTK makes use of these in some internal classes, like FreqDist

Common Graphing Operations

Line Graphs

Scatter Plots

Box plots

Box and whisker plots

Histograms

Things that all graphs need

Axis tick marks and scaling

Axis labels

Legends

Captions

Demos.

Plotting with python demo time.

Recognizing Textual Entailment

An example of a positive TE (text entails hypothesis) is:

- text: If you help the needy, God will reward you.
- hypothesis: Giving money to a poor man has good consequences.

An example of a negative TE (text contradicts hypothesis) is:

- text: If you help the needy, God will reward you.
- hypothesis: Giving money to a poor man has no consequences.

An example of a non-TE (text does not entail nor contradict) is:

- text: If you help the needy, God will reward you.
- hypothesis: Giving money to a poor man will make you better person.

http://aclweb.org/aclwiki/index.php?title=Textual_Entailment_Portal

Semantic understanding

Full, correct, human-like textual entailment is an AI-complete problem.

But how close can we get with lexical analysis?

British Left Waffles On Nukes

What is meaning?

This is a very difficult question, with many competing answers.

Sapir-Whorf hypothesis, Kripke, Saussure, Fodor, Margolis, Lakoff

Computational Semantics

There have been some attempts at computational approaches to semantics.

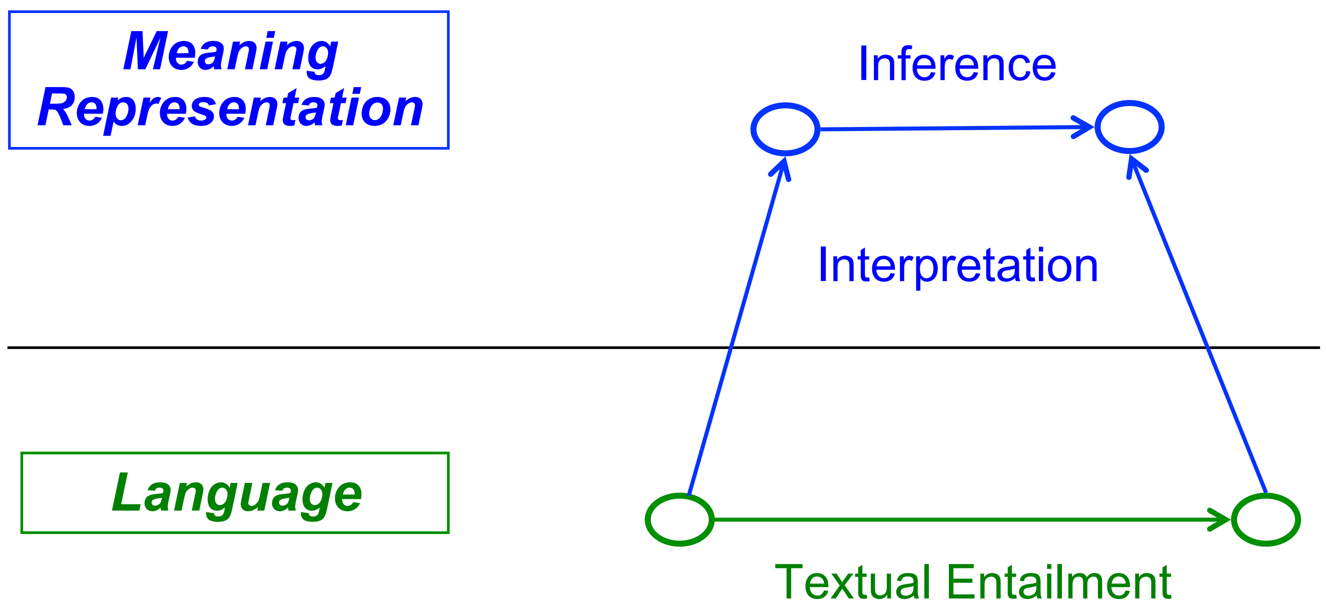
Some use internal semantic representations.

- For example, Information Extraction Frames.

More often there are not explicit representations

- Word sense disambiguation
- Named entity recognition
- Semantic role labeling.

Inference



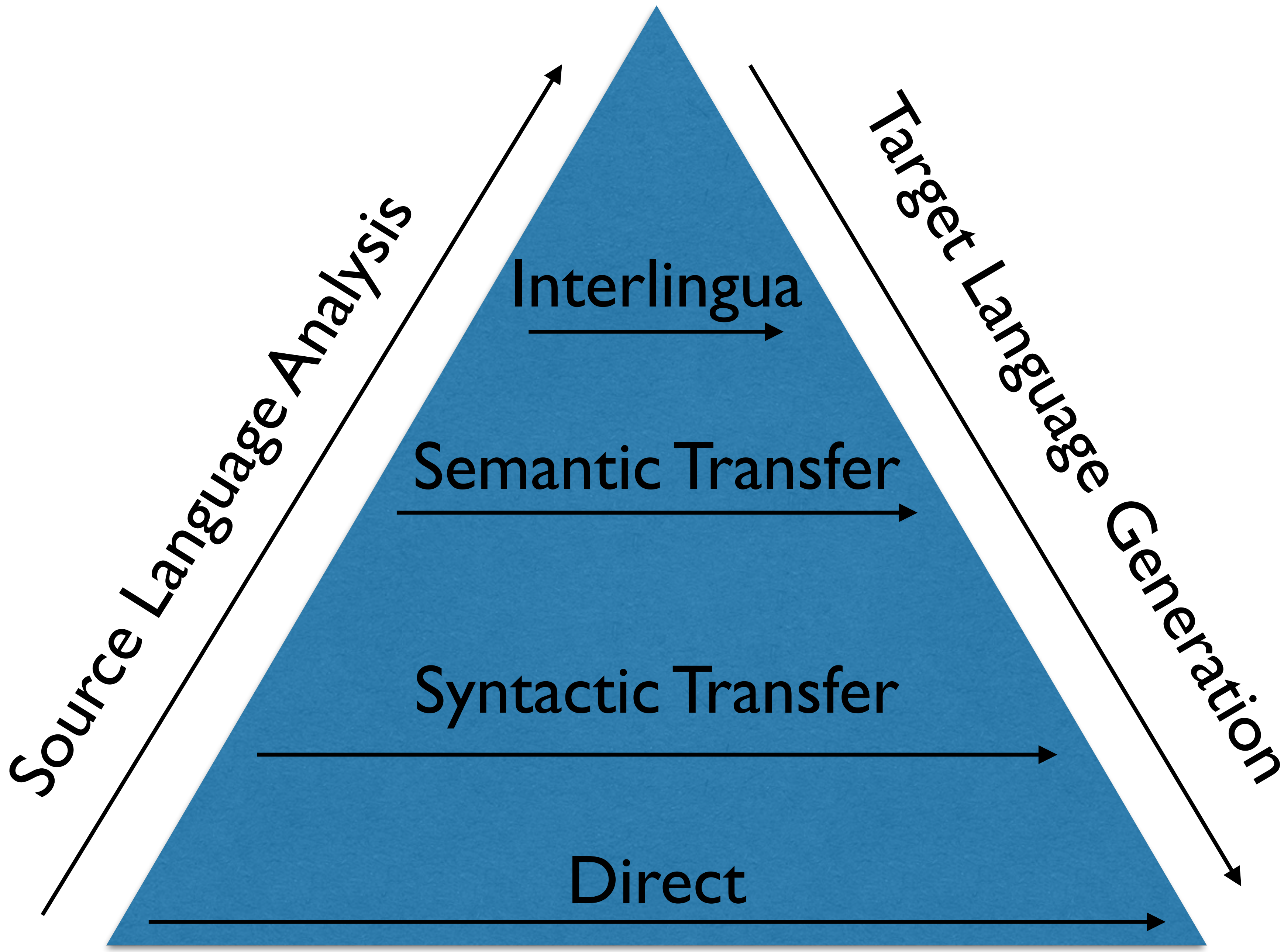
Humans do inference in a meaning space.

In most computational applications, textual entailment is performed.

This is very related to machine translation

Aside: Machine Translation Pyramid

aka The Vauquois Triangle



Textual entailment

A relationship between two text fragments, a Text (t) and hypothesis (h)

t entails h ($t \rightarrow h$) if
humans reading t will infer that h is **most likely** true

Contradiction

A relationship between two text fragments, a Text (t) and hypothesis (h)

h contradicts t if
the relations/events described by h are **highly unlikely to be true** given the relations/events described by T

Example

Text:

The purchase of Houston-based LexCorp by BMI for $2Bn prompted widespread sell-offs by traders as they sought to minimize exposure. LexCorp had been an employee-owned concern since 2008.

Hyp 1: BMI acquired an American company.

Hyp 2: BMI bought employee-owned LexCorp for $3.4Bn.

Hyp 3: BMI is an employee-owned concern.

Approaches to Textual Entailment

1. Lexical
2. Tree Similarity
3. Predicate-argument structures
4. Logical form
5. Learning Alignment

Lexical

1. Bag-of-words model: words (and possibly NEs) form the lexical constituents
2. For each word in H, find “best” word in T
3. Normalize scores across sentence-pairs
4. Find a threshold to distinguish the good matches from the bad matches

How do you measure similarity?

1. bought (v) ↔ purchase (n)
2. How to compare numeric quantities?
   - “$2 Bn” and “under $3.4 Bn”

Solutions:

- Define similarity metrics between words and NEs
  - word similarity based on WordNet (or a continuous space representation)
  - NE similarity based on rules (acronyms, abbreviated first names, etc.)

Similarity metrics for Numeric Quantities (NQs)

- Tokenize, find units, and compare

Tree Similarity

Syntactic parse or other tree edit distance from T to H.

- Needs to be augmented to work well.

String Edit distance

- Edit operations on characters
- Levenshtein distance

Token Edit distance

- Edit operations over sequence of tokens in Text and Hyp
- Levenshtein over tokens

Tree Edit distance

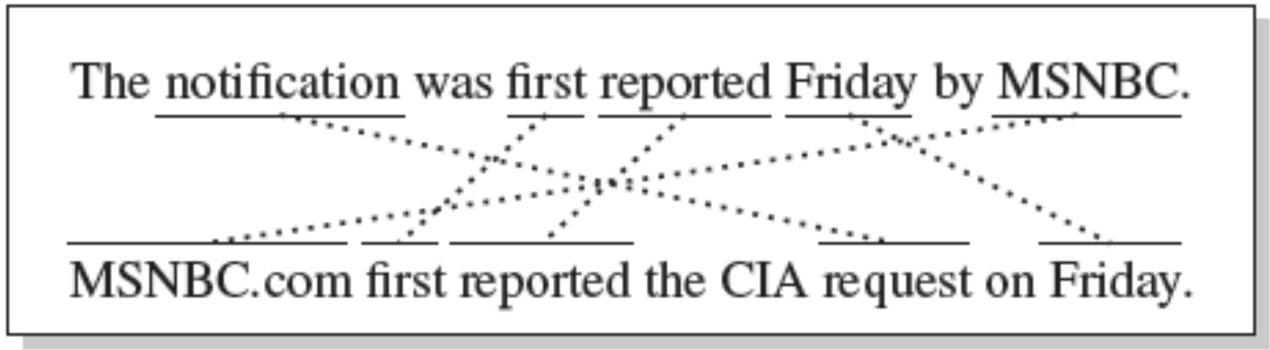
- Edit operations over nodes of syntactic representation of Text and Hyp

Predicate-argument structure

Similarity defined over semantic structure of sentences, including arity of relation verbs, core arguments, and sentence passivization.

Lexical similarity augmented with roles played by semantic units in the pair of sentences

Shallow Lexical alignment may help focus predicate-argument match to relevant sub-structures



Logical Form

Transform Text to logic-based representation

Infer Hyp using a theorem prover

Bag-of-words alignment used to backoff

Includes dependency parsing, POS, Coref

Uses WordNet and other rules to generate a chain of reasoning from T to H

- Limited by errors in knowledge sources

Learning Alignment

Idea: break entailment into smaller decisions

Alignment as a way to recognize relevant Text portions

Portions of text compared using closed set of operations

- Operations include lexical similarity, structural similarity
- Possible to define concepts such as semantic containment and semantic exclusion
- May be extended using Knowledge bases

Entailment relations

symbol	name	example
$P = Q$	equivalence	*couch* = *sofa*
$P \sqsubset Q$	forward entailment (strict)	*crow* $\sqsubset$ *bird*
$P \sqsupset Q$	reverse entailment (strict)	*European* $\sqsupset$ *French*
$P \wedge Q$	negation (exhaustive exclusion)	*human* $\wedge$ *nonhuman*
$P \mid Q$	alternation (non-exhaustive exclusion)	*cat* $\mid$ *dog*
$P \smile Q$	cover (exhaustive non-exclusion)	*animal* $\smile$ *nonhuman*
$P \# Q$	independence	*hungry* # *hippo*

Projection of entailment

Find sequence of edits connecting *P* and *H*

- Insertions, deletions, substitutions, …

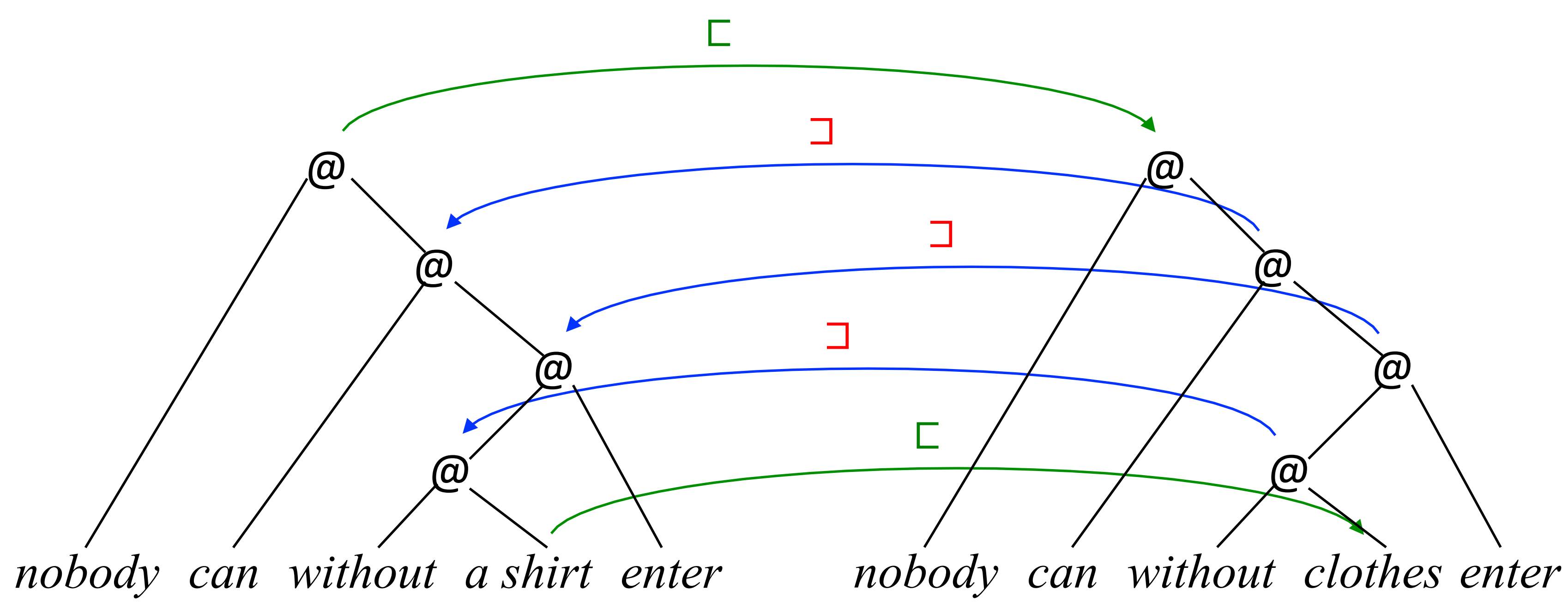
Determine lexical entailment relation for each edit

- Substitutions: depends on meaning of substituted terms: *cat* | *dog*
- Deletions: ⊏ by default: *red socks* ⊏ *socks*
- But some deletions are special: *not ill* ^ *ill, refuse to go* | *go*
- Insertions are symmetric to deletions: ⊐ by default

Project up to find entailment relation across each edit

Compose entailment relations across sequence of edits

- similar to Tarski's relation algebra



Textual Entailment

Semantic analysis based on surface and some deeper features

Many approaches, not quite full semantic understanding, but useful efforts.

Next Time

Recap

Course Recap

Probabilities and Statistics

- FreqDist, ConditionalFreqDist

Regular Expressions (Practice makes perfect)

List comprehensions

Recursion

Dynamic Programming

Machine Learning with Python

- **Never Never Never Test on Training Data**

Tagging with NLTK

Thank you