Distributional Semantic Models for Affective Text Analysis and Grammar Induction

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References

[1] E. Iosif and A. Potamianos. 2010. “Unsupervised semantic similarity computation between terms using web documents”. IEEE Transactions on Knowledge and Data Engineering.
[2] E. Iosif and A. Potamianos. 2013. “Similarity computation using semantic networks created from web-harvested data”. Natural Language Engineering.
[3] N. Malandrakis, A. Potamianos, E. Iosif and S. Narayanan. 2013. “Distributional Semantic Models for Affective Text Analysis”. IEEE Transactions on Audio, Speech and Language Processing.
[4] K. Zervanou, et al. 2014. “Word Semantic Similarity for Morphologically Rich Languages”. In Proc. LREC.
[5] N. Malandrakis et al. 2014. “Affective language model adaptation via corpus selection”. In Proc. ICASSP.
[6] G. Athanasopoulou, E. Iosif and A. Potamianos. 2014. “Low-Dimensional Manifold Distributional Semantic Models”. In Proc. COLING.
[7] S. Georgiladakis et al. 2014. “Fusion of knowledge-based and data-driven approaches to grammar induction". In Proc. Interspeech.
[8] S. Georgiladakis et al. 2015. “Fusion of Compositional Network-based and Lexical Function Distributional Semantic Models". In Proc. NAACL Wkshp on Cognitive Modeling and Computational Linguistics (CMCL 2015).

Talk Outline

- Motivation: Cognitive Semantic Models
- Semantic similarity estimation
  - Web data harvesting
  - Network-based Distributional Semantic Models (DSMs)
  - Hierarchical manifold DSMs
- Semantic-affective models of text
  - Affective lexica and semantic-affective maps
  - Compositional semantics and affect
  - Affective model adaptation
- PortDial and SpeDial project overview
  - Grammar induction
  - Web data harvesting
  - SemEval 2014 task on grammar induction

List of Open Questions

1. How are concepts, features/properties, categories, actions represented?
2. How are concepts, properties, categories, actions combined (compositionally)?
3. How are judgements (classification/recognition decisions) achieved?
4. How is learning and inference (especially induction) achieved?

Answers should fit evidence by psychology and neurocognition!

Three Solutions

- Symbolic
  - cognition is a Turing machine
  - computation is symbol manipulation
  - rule-based, deterministic (typically)
- Associationism, especially, connectionism (ANNs)
  - brain is a neural network
  - computation is activation/weight propagation
  - example-based, statistical, unstructured (typically)
- Conceptual
  - intermediate between symbolic and connectionist
  - concepts are represented as well-behaved (sub-)spaces
  - computation tools: similarity, operators, transformations
  - hierarchical, semi-structured

Properties of the Three Approaches

- Symbolic
  - Good for high-level cognitive computations (math)
  - Poor generalization power
  - Too expensive and slow for most cognitive purposes
- Conceptual
  - Excellent generalization power (intuition, physics)
  - Good for induction and learning; geometric properties (hierarchy, low dim., convex) guarantee quick convergence
  - Properties and actions defined as operators/translations
  - Still too slow for some survival-dependent decisions
- Connectionist (machine learning)
  - General-purpose, extremely fast and decently accurate
  - Computational sort-cuts create cognitive biases
  - Poor generalizability power due to high dimensionality and lack of crisp semantic representation

Representation Learning

- Properties of a classifier with good generalization properties [Bengio et al 2013]:
  - Low-dimensionality/Sparseness
  - Distributed representations/hierarchy
    - Depth and abstraction
  - Shared factors across tasks
- Examples: auto-encoders, manifolds, deep neural nets ...
- How to induce these properties in your classifiers:
  - Include as regularization term in training classifier criterion
  - Include properties directly in classifier design
  - Go deep and pray (dirty neural net tricks)

Our Vision

- Cognitively-motivated semantic models
  - Emphasis on induction not classification
  - Associations not probabilities/distance
  - Mappings between layers
  - Hierarchical manifold models not metric spaces
  - Multimodal not unimodal
  - Other cognitive considerations ...

Problem Definition

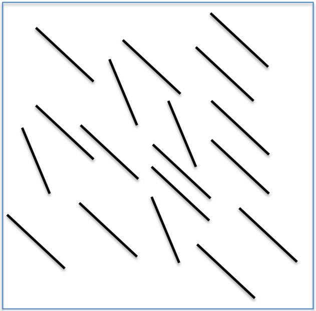
- Semantic Similarity Computation
  - Given a pair of words or terms (w_i, w_j)
  - Compute semantic similarity between them $S(i, j)$
- Related tasks
  - Phrase or sentence level semantic similarity
  - Strength of associative relation between words
  - Affective score (valence) of words and sentences
- Motivation
  - Organizing principle of human cognition
  - Building block of machine learning in NLP/semantic web
  - Entry point for the semantics of language

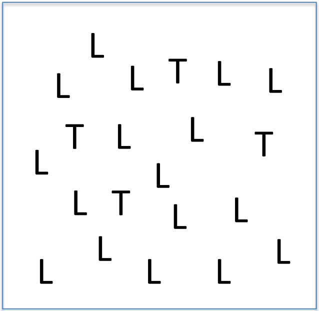
System 1 vs System 2

- Using Kahneman's (and others) formalism:
  - System 1 (intuition): generates
    - impressions, feelings, and inclinations
  - System 2 (reason): turns System 1 input into
    - beliefs, attitudes, and intentions
- Associative relations reside in System 1
- But where do semantic relations reside?

Example

- Example from vision: system 1 vs system 2



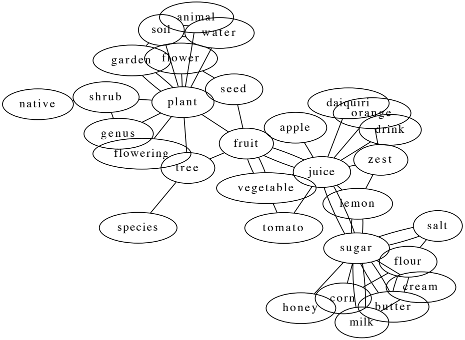


Main approaches of lexical semantics

- Word are associated with feature vectors
  - crisp, parsimonious representation of semantics
- Distributional semantic models (DSMs)
  - Semantic information extracted from word frequencies
  - Estimate co-occurence counts of word pairs or triplets
  - Estimate statistics of word context vectors
- Semantic networks
  - discovery of new relations via systematic co-variation
  - robust estimates – smoothing corpus statistics over network
  - rapid language acquisition

Example of Semantic Network

- Linked nodes: lexicalized senses and attributes
  - Informative for semantic similarity computation
- Computation of structural properties, e.g., cliques



Proposed semantic similarity two-tier system

- Unifies the three approaches
- Fuzzy vs explicit semantic relations
- Word senses vs words vs concepts
- A two tier system
  - An associative network backbone
  - Semantic relations defined as operations on network neighborhoods (cliques)
- Consistent with system 1 vs system 2 view
- Furthermore we believe that the
  - underlying network consists of word senses, and
  - is a low dimensional semi-metric space

Semantic Similarity Estimation by Machines

- Resource-based, e.g., WordNet
  - Require expert knowledge
  - Not available for all languages
- Corpus-based
  - Distributional semantic models (DSMs)
  - Unstructured (unsupervised): no use of linguistic structure
  - Structured: use of linguistic structure
  - Pattern-based, e.g., Hearst patterns
- Mixed

Semantic Sim. Computation: Sense Similarity

- Maximum sense similarity assumption *[Resnik, '95]*:
  - Similarity of words equal to similarity of their closest senses
  - If words are considered as sets of word senses, this is the "common sense" set distance
- Given words w_1, w_2 with senses s_{1i}, s_{2j}

$$S(w_1, w_2) = \max_{ij} S(s_{1i}, s_{2j})$$

Semantic Sim. Computation: Attributional Similarity

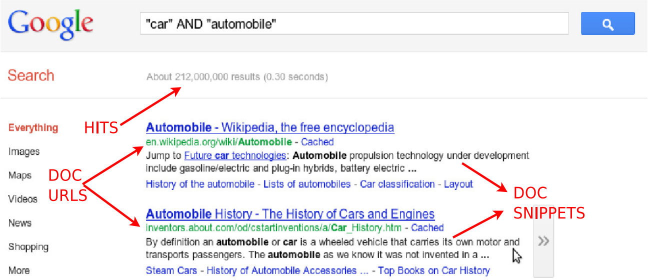
Attributional similarity assumption

- Attributes (features) reflect semantics
  - Item-Relation-Attribute, e.g., canary-color-yellow
- Main representation schemes
  - Hierarchical/Categorical
    - Mainly taxonomic relations, e.g., IsA, PartOf
  - Distributed (networks)
    - Open set of relations, e.g., Cause-Effect, etc
- Similarity between words
  - Function of attribute similarity
  - Defined wrt representation

Types of Similarity Metrics

- Co-occurrence-based
  - Assumption: co-occurrence implies relatedness
  - Co-occurrence counts: web hits, corpus-based
  - Examples: Dice coef., point-wise mutual information, ...
- Context-based
  - Assumption: context similarity implies relatedness (distributional hypothesis of meaning)
  - Contextual features extracted from corpus
  - Examples: Kullback-Leibler divergence, cosine similarity, ...
- Network-based (proposed)
  - Build lexical net using co-occurrence and/or context sim.
  - Notion of semantic neighborhoods
  - Assumptions: neighborhoods capture word semantics

Queries to Web Search Engines



- Number of hits
- Document URLs (download)
- Document snippets

Corpus Creation using Web Queries

- Two types of web queries
  - AND, e.g., "money + bank"
    "... leading **bank** in India offering online **money** transfer ..."
  - IND, e.g., "bank"
    "... downstream parallel to the **banks** of the river ..."
- AND queries
  - Pros: Similarity computation highly correlated (0.88) with human ratings *[Iosif & Potamianos, '10]*
  - Cons: Quadratic query complexity wrt lexicon *L*
- IND queries
  - Pros: Linear query complexity wrt lexicon *L*
  - Cons: Sense ambiguity: moderate correlation (0.55)

Semantic Similarity Estimation

- Co-occurence based metrics
  - From web: hits of IND, AND queries
  - From (web) corpus: co-occurence counts at the snippet or sentence level
  - Metrics: Dice, Jacard, Mutual Information, Google
- Context-based metrics
  - Download a corpus of documents of snippets using IND queries
  - Construct lexical context vector for each word (window ± 1)
  - Cosine similarity using binary or log-weighted counts

Enter semantic networks

- Why do IND queries fail to achieve good performance?
  1. Word senses are often semantically diverse
     - co-occurrence acts as a semantic filter
  2. Word senses have poor coverage in IND queries
     - rare word senses of words not well-represented
- Solution: use semantic networks
  1. Create a corpus for all words in lexicon (not just semantic similarity pair)
  2. Use semantic neighborhoods for semantic cohesion
     - improved robustness
  3. Inverse frequency word-sense discovery
     - discover rare senses via co-occurrence with infrequent words

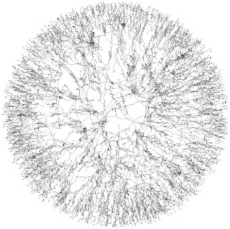
Corpus and Network Creation

- Goals
  - Linear web query complexity for corpus creation
  - New similarity metrics with high performance
- Proposed method
  - IND queries to aggregate data for large L ($\approx 9K$)
  - Create network and semantic neighborhoods
  - Neighborhood-based similarity metrics
- Advantages
  - Network: parsimonious representation of corpus statistics
  - Smooth distributions
  - Rare words: well-represented
  - Enable discovery of less frequent senses

Lexical Network - Semantic Neighborhoods

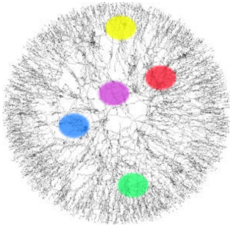
Lexical Network

- Undirected graph $G = (N, E)$
  - Vertices N: words in lexicon L
  - Edges E: word similarities



Semantic Neighborhoods

- For word i create subgraph G_i
- Select neighbors of i
  - Compute $S(i, j), \forall\, j \in L, i \neq j$
  - Sort j according to $S(i, j)$
  - Select $|N_i|$ top-ranked j



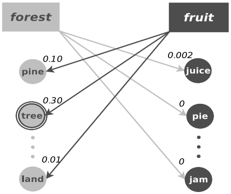
Semantic Neighborhoods: Examples

Word	Neighbors
automobile	**auto**, truck, **vehicle**, **car**, **engine**, bus, . . .
car	truck, **vehicle**, travel, service, **price**, **industry**, . . .
slave	slavery, beggar, **nationalism**, society, **democracy**, **aristocracy**, . . .
journey	**trip**, holiday, **culture**, **travel**, **discovery**, **quest**, . . .

- Synonymy
- Taxonomic: IsA, Meronymy
- Associative
- Broader semantics/pragmatics
- . . .

Neighborhood-based Similarity Metrics: M_n

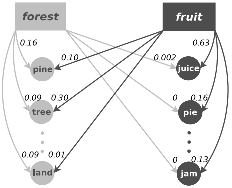
M_n metric: maximum similarity of neighborhoods



- Motivated by maximum sense similarity assumption
  - Neighbors are semantic features denoting senses
  - Similarity of two closest senses
- Select max. similarity: $M_n(\text{"forest"}, \text{"fruit"}) = 0.30$

Neighborhood-based Similarity Metrics: R_n

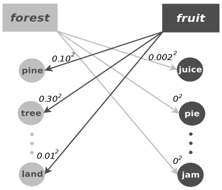
R_n metric: correlation of neighborhood similarities



- Motivated by attributional similarity assumption
  - Neighborhoods encode word attributes (or features)
  - Similar words have co-varying sim. wrt their neighbors
- Compute correlation r of neighborhood similarities
  - $r_1((0.16 \ldots 0.09), (0.10 \ldots 0.01)), r_2((0.002 \ldots 0), (0.63 \ldots 0.13))$
- Select max. correlation: $R_n(\textit{"forest"}, \textit{"fruit"}) = -0.04$

Neighborhood-based Similarity Metrics: metric $E_n^{\theta=2}$

$E_n^{\theta=2}$ metric : sum of squared neighborhood similarities



- Motivation: middle road between M_n and R_n
  - Accumulation of word–to–neighbor similarities
  - Non-linear weighting of similarities via $\theta = 2$
- $E_n^{\theta=2}$(“forest”, “fruit”)= $\sqrt{(0.10^2 + \cdots + 0.01^2) + (0.002^2 + \cdots + 0^2)} = 0.22$

Performance of net-based similarity metrics

- Task: similarity judgment on noun pairs
- Dataset: MC *[Miller and Charles, 1998]*
- Evaluation metric: Pearson's correlation wrt to human ratings

Dataset	Neighbor selection	Similarity computation	Metrics		
			$M_{n=100}$	$R_{n=100}$	$E_{n=100}^{\theta=2}$
MC	co-occur.	co-occur.	0.90	0.72	**0.90**
MC	co-occur.	context	**0.91**	0.28	0.46
MC	context	co-occur.	0.52	**0.78**	0.56
MC	context	context	0.51	0.77	0.29

Main findings

- Network construction
  - Co-occurence metrics achieve high-recall for word senses
  - Context-based metrics achieve high-recall for attributes
- Semantic similarity performance
  - Co-occurence a more robust feature that context
  - Max sense similarity assumption is valid and gives best performance
  - Attributional similarity assumption valid for certain cases/languages

Performance of web-based similarity metrics

- For MC dataset

Feature	Description	Correlation
context	AND queries	0.88
context	IND queries	0.55
context	IND queries: network	0.90

- Comparable to structured DSMs, WordNet-based approaches

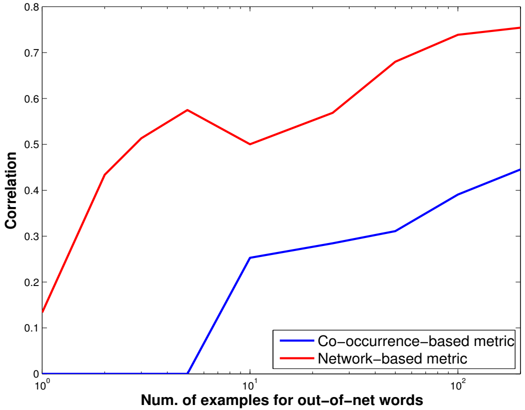
Extensions

- Sentence level semantic similarity (SemEval 2012, 2013)
- Abstract vs concrete semantic networks (IWSC 2013)
- Morphologically rich languages (LREC 2014)
  - Network-based DSMs perform consistently well across languages
- Network DSMs and language acquisition (BabyAffect project)
  - Recognition vs generalization power (induction)
- Manifold DSMs
- Multimodal (text and image) conceptual spaces
- Compositional Network-based Distributional Semantic Models (CMCL 2015)

Acquisition of lexical semantics

- Assume a recently acquired word *w*
  - Num. of *w*'s examples needed for "learning" *w*'s similarities
  - Related to acquisition of lexical semantics
- Compare
  - Simple co-occurrence-based similarity metric
  - Network-based similarity metric
- Experiment
  - 28 noun pairs (Miller-Charles dataset)
  - Remove one word from each pair from the network
  - Compute pair similarities
  - Evaluation: correlation coef. wrt human similarity ratings

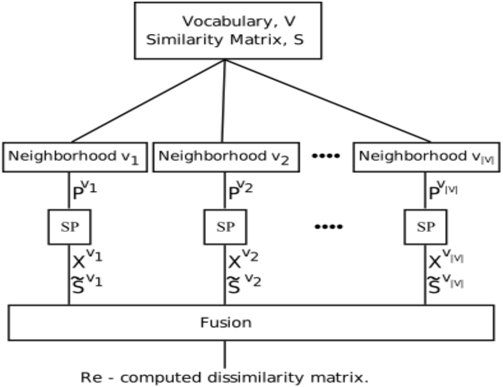
Acquisition of lexical semantics



Manifold DSMs

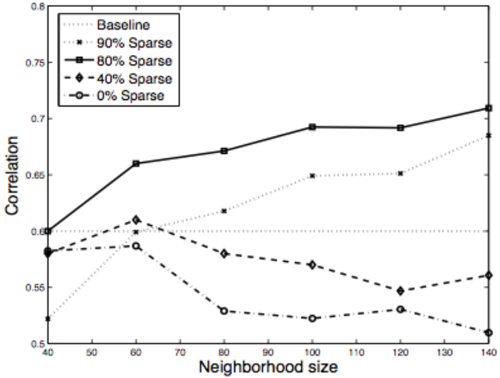
- Cognitive semantic space is fragmented in domains
- Sparse encoding of relations in each domain (manifold)
- Low-dimensional subspaces with good geometric properties
  - vs non-metric global semantic space
- Semantic similarity operation is performed locally in each subspace
- Decision fusion to reach semantic similarity score

Manifold DSMs

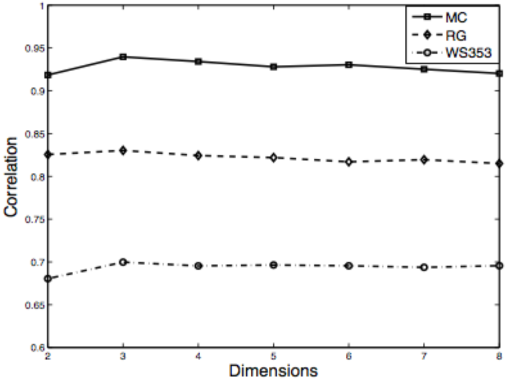


Sparse similarity matrices

- Correlation performance on the WS363 task



Effect of dimensionality



Net-based Models: Definition

Network model using similarities to describe associations

1. Activation Layer: Most similar lexical units and relations to target constitute its semantic neighborhood
2. Similarity Layer: Neighborhoods utilized to compute similarity

Motivation: Activation Triggering

- Target word activates set of words sharing same domain and/or meaning (e.g., “duck” $\Leftrightarrow$ “lake”)
- Set embodies target word’s meaning

Extension of net-based DSMs of [Iosif and Potamianos ’15]

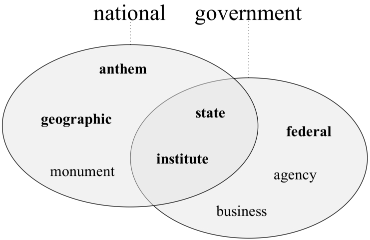
Net-based Models: Activation Layer

Let $i = (i_1 \; i_2)$, with N_{i_1}, N_{i_2} being neighborhoods of i_1, i_2.

- Scheme 1: Intersection. Augment sizes of N_{i_1} and N_{i_2} until a minimum size θ is achieved for $N_{i_1} \cap N_{i_2}$
- Scheme 2: Union. The composed neighborhood is derived by taking the union $N_{i_1} \cup N_{i_2}$
- Scheme 3: Most similar. Given $n_m \in N_{i_1} \cup N_{i_2}$, the members $\{n_1, ..., n_m, ..., n_\theta\}$ of N_i are selected based on their average semantic similarity wrt. i_1 and i_2

Network-based Models: Extending the Activation Layer

Let $i = (i_1 \ i_2)$, with N_{i_1}, N_{i_2} and N_i being the neighborhoods of i_1, i_2, and i.



- Scheme 1: Intersection. Augment sizes of N_{i_1} and N_{i_2} until a minimum size θ is achieved for N_i

Net-based Models: Similarity Layer

Three more metrics to estimate similarity of i and j:

- Average of top-k similarities M_k: Extends the M metric by smoothing similarity over the top k scores
- Average of top-k pairwise similarities P_k: Averages similarity over the top k pairwise similarities across N_i and N_j members.
- Hausdorff-based similarity H: motivated by the Hausdorff distance [4], similarity is computed as:

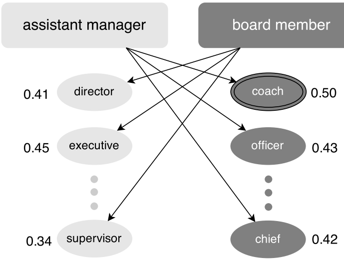
$$H(i,j) = \max\{h(N_i, N_j), h(N_j, N_i)\}, \tag{1}$$

where

$$h(N_i, N_j) = \min_{x \in N_i}\{\max_{y \in N_j}\{S(x,y)\}\}, \tag{2}$$

$S(.)$ being a metric of semantic similarity.

Network-based Models: Similarity Layer
Maximum Similarity Metric



- Neighborhoods encode senses possibly shared by constituents
- Similarity can be estimated by considering their closest senses

Fusing Net-based with Transformational Models

Lexical Function: Modifications are linear transformations (functions) on VSMs via matrix-by-vector multiplication [2,5]:

$$f(\alpha) =_{def} F \times a = b, \tag{3}$$

a: vector representation of argument α
b: compositional vector output
F: matrix-encoded function f, learnt by regressing on observed input (head) and output (phrase) representations

Fusion of DSMs

- Some modifiers apply an effect on the head noun meaning while others act as simple composition constituents
- Combine models to weight their goodness of fit utilizing the transformative degree T

[2] M. Baroni and R. Zamparelli 2010. Nouns are vectors, adjectives are matrices: Representing adjective-noun

Fusion of Distributional Semantic Models

$T(i,j)$: estimated using i_1 and j_1 modifiers' training Mean Squared Error (MSE) as

$$T(i,j) = \frac{1}{2}(MSE(i_1) + MSE(j_1)). \tag{4}$$

Fusion of lexical function with net-based model defined as

$$\Phi^{lf}_{net}(i,j) = \lambda(i,j)\ S_N + (1 - \lambda(i,j))\ S_{LF}, \tag{5}$$

S_N, S_{LF}: net-based and lexical function model scores
λ: computed using a sigmoid function as:

$$\lambda(i,j) = 0.5/\left(1 + e^{-T(i,j)}\right) \tag{6}$$

%section[Experiments and Results]Experiments and Results

Evaluation and Results

Model	**NN**	**AN**	**VO**
add (nmf300)	**.67**	**.61**	.53
add (svd300)	.63	.59	**.59**
lf (nmf300, Ridge)	**.76**	**.46**	**.35**
lf (svd300, Ridge)	.63	.35	.26
M (Intersection)	.56	.46	.37
M' (Intersection)	.61	**.57**	**.47**
$M_{k=3}$ (Intersection)	**.64**	.51	.41
$P_{k=3}$ (Most-similar)	.63	.46	.23
H (Intersection)	.58	.39	.26
fusion Φ^{lf}_{net}	**.80**	.54	.35
fusion Φ^{lf}_{add}	.76	**.57**	**.44**

Table: Performance on 108 noun-noun, adjective-noun, and
verb-object phrase pairs [Mitchell & Lapata '10] (Spearman

Contributions

Proposed a language agnostic, unsupervised and scalable algorithm for semantic similarity computation

- No linguistic knowledge required, works from text corpus or using a web query engine
- Shown to perform at least as well as resource-based semantic similarity computation algorithms, e.g., WordNet-based methods

Compositional Semantic-Affective Models of Text

Motivation

- Affective text labeling at the core of many multimedia applications, e.g.,
  - Sentiment analysis
  - Spoken dialogue systems
  - Emotion tracking of multimedia content
- Affective lexicon is the main resource used to bootstrap affective text labeling
  - Lexica are currently of limited scope and quality

Goals and Contributions

Our goal: assigning continuous high-quality polarity ratings to any lexical unit

- We present a method of expanding an affective lexicon, using web-based semantic similarity
- Assumption: semantic similarity implies affective similarity.
- The expanded lexica are accurate and broad in scope, e.g., they can contain proper nouns, multi-word terms

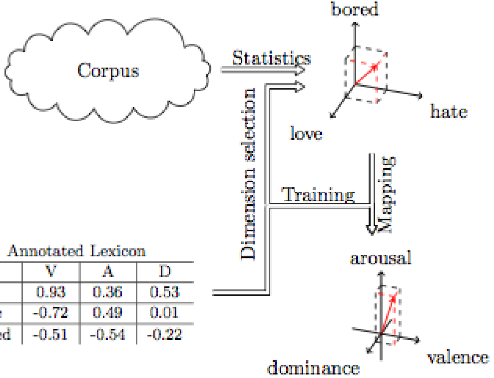
Our lexicon expansion method

Extension of [Turney and Littman, '02].
Assumption: the valence of a word can be expressed as a linear combination of the valence ratings of seed words weighted by semantic similarity and trainable weights a_i :

$$\hat{v}(t) = a_0 + \sum_{i=1}^{N} a_i \; v(w_i) \; d(w_i, t), \tag{7}$$

- t : a word or n-gram (token) not in the affective lexicon
- $w_1 ... w_N$: seed words
- $v(.)$: valence rating of a word or n-gram
- a_i : weight assigned to seed w_i
- $d(w_i, t)$: semantic similarity between word w_i and token t

Semantic-Affective Mapping



Annotated Lexicon

	V	A	D
love	0.93	0.36	0.53
hate	-0.72	0.49	0.01
bored	-0.51	-0.54	-0.22

Given

- an initial lexicon of K words
- a set of $N < K$ seed words

we can use (7) to create a system of K linear equations with $N + 1$ unknown variables:

$$\begin{bmatrix} 1 & d(w_1, w_1)v(w_1) & \cdots & d(w_1, w_N)v(w_N) \\ \vdots & \vdots & \vdots & \vdots \\ 1 & d(w_K, w_1)v(w_1) & \cdots & d(w_K, w_N)v(w_N) \end{bmatrix} \cdot \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_N \end{bmatrix} = \begin{bmatrix} 1 \\ v(w_1) \\ \vdots \\ v(w_K) \end{bmatrix} \quad (8)$$

Solving with Least Mean Squares estimation provides the weights a_i.

Example, $N = 10$ seeds

Order	w_i	$v(w_i)$	a_i	$v(w_i) \times a_i$
1	mutilate	-0.8	0.75	-0.60
2	intimate	0.65	3.74	2.43
3	poison	-0.76	5.15	-3.91
4	bankrupt	-0.75	5.94	-4.46
5	passion	0.76	4.77	3.63
6	misery	-0.77	8.05	-6.20
7	joyful	0.81	6.4	5.18
8	optimism	0.49	7.14	3.50
9	loneliness	-0.85	3.08	-2.62
10	orgasm	0.83	2.16	1.79
-	w_0 *(offset)*	1	0.28	0.28

Sentence Tagging

Simple combinations of word ratings:

- linear (average)

$$v_1(s) = \frac{1}{N}\sum_{i=1}^{N} v(w_i)$$

- weighted average

$$v_2(s) = \frac{1}{\sum\limits_{i=1}^{N} |v(w_i)|}\sum_{i=1}^{N} v(w_i)^2 \cdot \mathrm{sign}(v(w_i))$$

- max

$$v_3(s) = \max_i(|v(w_i)|) \cdot \mathrm{sign}(v(w_z)), \quad z = \arg\max_i(|v(w_i)|)$$

N-gram Affective Models

- Generalize method to n-grams

$$v_i(s) = a_0 + a_1 v_i(unigram) + a_2 v_i(bigram)$$

- Starting from all 1-grams and 2-grams, select terms:
  1. Backoff: use overlapping bigrams as default, revert to unigrams based on mutual information-based criterion
  2. Weighted interpolation: use all unigrams and bigrams as default, reject bigrams based on criterion
- In both cases unigrams and bigrams are given linear weights, trained using LMS

Evaluation

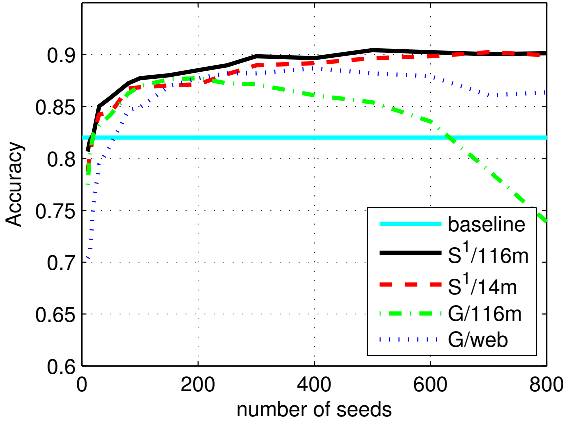
- ANEW Word Polarity Detection Task
  - Affective norms for English words (ANEW) corpus
  - 1.034 English words, continuous valence ratings
- General Inquirer Word Polarity Detection
  - General Inquirer words corpus
  - 3.607 English words, binary valence ratings
- BAWLR Word Polarity Detection Task
  - Berlin affective word list reloaded (BAWLR) corpus
  - 2.902 German words, continuous valence ratings
- SemEval 2007 Sentence Polarity Detection
  - SemEval 2007 News Headlines corpus
  - 1.000 English sentences, continuous valence ratings
  - ANEW used for lexicon training
  - 250 sentence development set used for word fusion training
- SemEval 2013, 2014: Twitter Sentiment Analysis

Experimental Procedure

- Corpus selection
  - Web corpus (web)
  - Lexically balanced web corpus (14m, 116m)
- Semantic Distance
  - Co-occurence based (G = google)
  - Context-based using web snippets (S)
- All experiments: training on ANEW seed words (cross-validation)

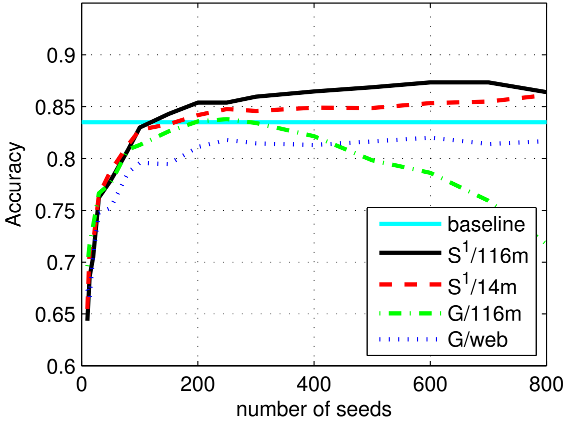
Word Polarity Detection (ANEW)

2-class word classification accuracy (positive vs negative)



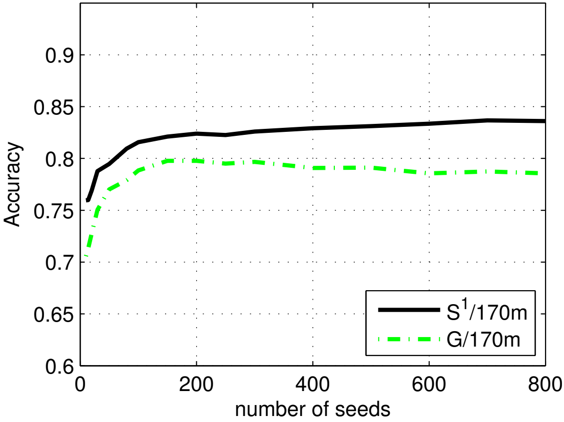
Word Polarity Detection (GINQ)

2-class word classification accuracy (positive vs negative)



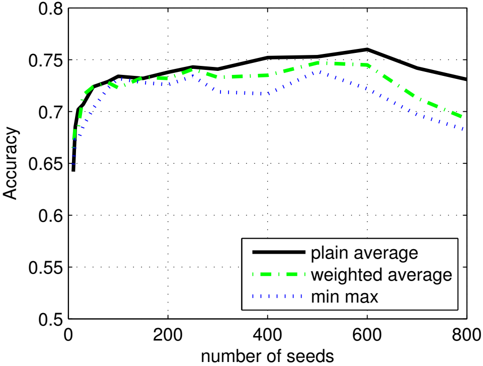
Word Polarity Detection (BAWLR)

2-class word classification accuracy (positive vs negative)



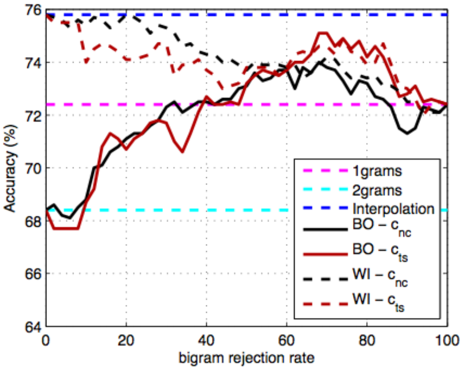
Sentence Polarity Detection (SemEval 2007)

2-class sentence classification accuracy (positive vs negative), using weighted interpolation



Sentence Polarity Detection (SemEval 2007)

2-class sentence classification accuracy (positive vs negative), vs bigram rejection threshold

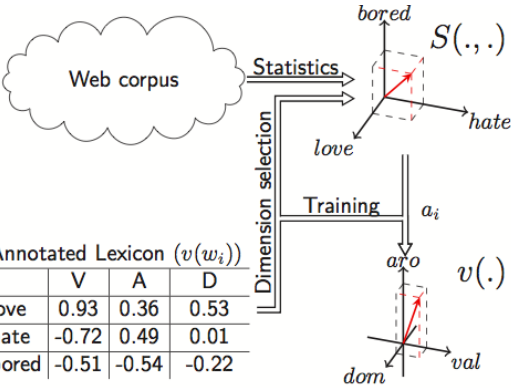


ChIMP Sentence Frustration/Politeness Detection

- ChIMP Children Utterances corpus
- 15.585 English sentences, Politeness/Frustration/Neutral ratings
- SoA results, binary accuracy P vs 0 / F vs O:
  - 81% / 62.7% [Yildirim et al, '05]
- 10-fold cross-validation
- ANEW used for training/seeds to create word ratings
- ChiMP words added to ANEW with weight *w*, to adapt to the task
- Similarity metric: Google semantic relatedness
- Only content words taken into account

Politeness: Sentence Classification Accuracy	Fusion scheme		
	avg	w.avg	max
Baseline: P vs O	0.70	0.69	0.54
Adapt $w = 1$: P vs O	0.74	0.70	0.67
Adapt $w = 2$: P vs O	0.77	0.74	0.71
Adapt $w = \infty$: P vs O	**0.84**	0.82	0.75
Frustration: Sentence Classification Accuracy	**Fusion scheme**		
	avg	w.avg	max
Baseline: F vs O	0.53	0.62	**0.66**
Adapt $w = 1$: F vs O	0.51	0.58	0.57
Adapt $w = 2$: F vs O	0.49	0.53	0.53
Adapt $w = \infty$: F vs O	0.52	0.52	0.52

Twitter Sentiment Analysis: Main Concept



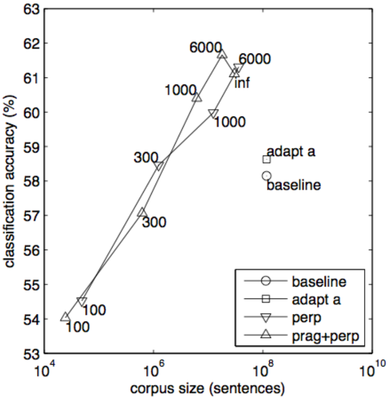
Annotated Lexicon ($v(w_i)$)

	V	A	D
love	0.93	0.36	0.53
hate	-0.72	0.49	0.01
bored	-0.51	-0.54	-0.22

$$\underbrace{\underset{0.12}{\text{I}}\ \underset{-0.71}{\text{hate}}\ \underset{0.41}{\text{you}}\ \underset{0.38}{\text{so}}\ \underset{0.31}{\text{much}}}_{\text{VAD Statistics} \Rightarrow \text{Classifier} \Rightarrow \text{Anger} = \text{TRUE}}$$

Twitter Sentiment Analysis: Semantic Adaptation

3-class sentence classification accuracy (positive-neutral-negative) [ICASSP 2014]

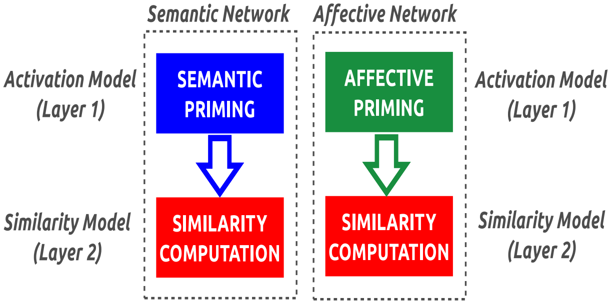


SemEval 2014: Twitter Sentiment Results Analysis

Features removed	LJ2014		SMS2013		TW2013		TW2014		TW2014SC	
	avg. F1	diff	avg. F1	diff	avg. F1	diff	avg. F1	diff	avg. F1	diff
None (Submitted)	69.3		57.0		**66.8**		67.8		57.3	
Lexicon-derived	43.6	-25.8	38.2	-18.8	49.5	-17.4	51.5	-16.3	43.5	-13.8
Emotiword	67.5	-1.9	56.4		63.5	-3.3	66.1	-1.7	54.8	-2.5
Base	68.4		56.3		65.0	-1.9	66.4	-1.4	**59.6**	2.3
Adapted	69.3		57.4		66.7		67.5		50.8	-6.5
Sentiment140	68.1	-1.3	54.5	-2.5	64.4	-2.4	64.2	-3.6	45.4	-11.9
NRC Tag	**70.6**	1.3	**58.5**	1.6	66.3		66.0	-1.7	55.3	-2.0
SentiWordNet	68.7		56.0		66.2		**68.1**		52.7	-4.6
per Lexeme	69.3		56.7		66.1		68.0		52.7	-4.5
per Lexeme-POS	68.8		57.1		66.7		67.4		55.0	-2.2
Semantic Similarity	69.0		58.2	1.2	64.9	-2.0	65.5	-2.2	52.2	-5.0
Punctuation	69.7		57.4		66.6		67.1		53.9	-3.4
Emoticon	69.3		57.0		**66.8**		67.8		57.3	
Contrast	69.2		57.5		66.7		67.0		51.9	-5.4
Prefix	69.5		57.2		**66.8**		67.2		47.4	-9.9
Suffix	68.6		57.2		66.5		67.9		56.3	

Semantic and Affective Networks

- Emotion conveys salient info. facilitating semantic process.
- Extension of net-based DSMs of *[Iosif&Potamianos]*



Similarity Computation: Experiments & Results

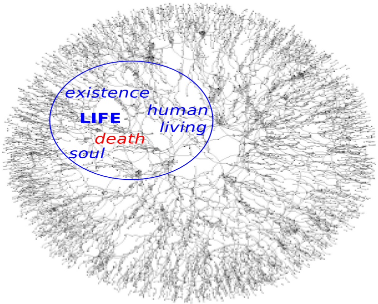
- Task: compute similarity between nouns
- Evaluation metric: correlation wrt human ratings

Type of feature for		Number of neighbors (n)				
Layer 1	Layer 2	10	30	50	100	150
MC dataset						
Lexical	Lexical	0.48	0.80	0.83	0.91	0.90
Affect	Lexical	0.85	0.91	0.88	0.85	0.83
WS353 dataset						
Lexical	Lexical	0.42	0.55	0.59	0.64	0.65
Affect	Lexical	0.63	0.68	0.68	0.65	0.63

- Affective similarity (layer 1) $\rightarrow$ semantic similarity (layer 2)!

Semantic Opposition

- Antonymy embodies both semantic proximity and distance
- Easily recognized by humans



- DSMs do not capture antonymy
  - E.g., "death" in the semantic neighborhood of "life"

Synonymy vs. Antonymy: Experiments & Results

- Task: classify noun pairs as synonymous or antonymous
- Dataset: 172 synonyms, 172 antonyms *[Mohammad et al.]*
- Classifier: Support Vector Machines with linear kernel
- 10-fold cross validation
- Evaluation metric: classification accuracy

Semantic relation	Random	Feature types	
		Lexical	Affective
Synonymy	50%	61%	62%
Antonymy	50%	61%	82%

Conclusions

Proposed a high-performing, robust, general-purpose and scalable algorithm for affective lexicon creation

- Investigated linear and non-linear sentence level fusion schemes, showing good but task-dependent performance
- Investigated domain adaptation: semantic space vs semantic-affective mapping adaptation
- Demonstrated that distributional approach can generalize to n-grams

Linguistic Resources for Spoken Dialogue Systems: The PortDial and SpeDial projects

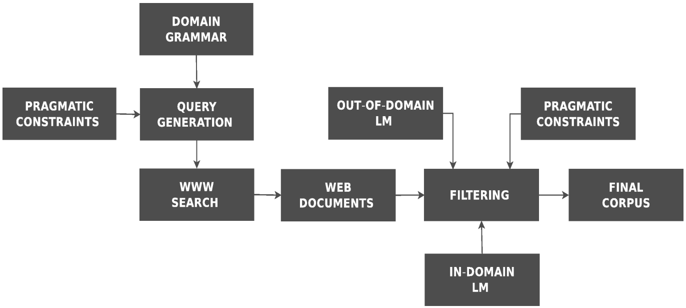
Outline

1. PortDial project
   - "Language Resources for Portable Multilingual Spoken Dialogue Systems"
   - 2-year EU-funded project: currently in last quarter
   - www.portdial.eu
2. SpedDial project
   - "Machine-Aided Methods for Spoken Dialogue System Enhancement and Customization for Call-Center Applications"
   - 2-year EU-funded project: currently in first quarter
   - www.spedial.eu
3. SemEval'14-Task 2
   - "Grammar Induction for Spoken Dialogue Systems"
   - Evaluation period: until March 30
   - http://alt.qcri.org/semeval2014/task2/

PortDial: Outline

- Grammars
  - Essential unit of spoken dialogue systems
  - Expertise needed, time-consuming
  - Need for rapid porting
- PortDial paradigm
  - Machine-aided process
  - Human-in-the-loop
- ProtDial approaches
  - Corpora creation via web harvesting
  - Grammar induction
    - Bottom-up: corpus-based
    - Top-down: ontology-based
    - Fusion of bottom-up and top-down

PortDial: Web-harvested corpora



- WWW search query, e.g., "depart from"&("flight"|"travel"|..)
- Out-of-domain LM: perplexity $\rightarrow$ grammaticality/spelling
- In-domain LM: perplexity $\rightarrow$ domain relevance

PortDial: Web-harvested corpora

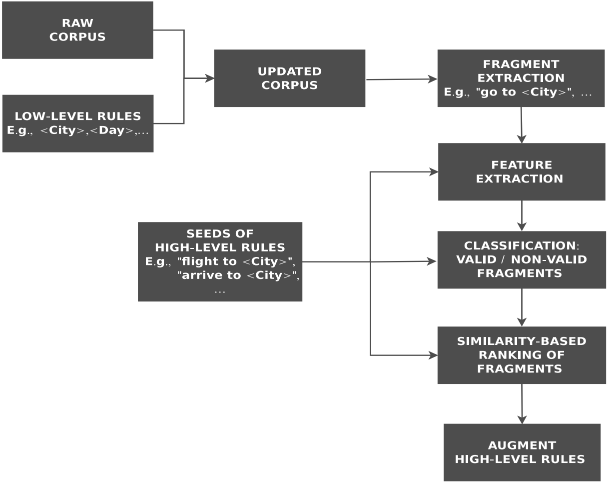
- Travel domain grammar
  - 83 low-level rules
    - E.g., <City> = (“New York”, “London”, ...)
  - 47 high-level rules
    - E.g., <ArrivalCity> = (“fly to <City>”, “arrive at <City>”, ...)
- Use of various corpora for inducing low-level rules

Corpus	Precision	Recall	F-measure
Q&A	0.52	0.40	0.45
WoZ	0.41	0.33	0.37
Human-Human	0.42	0.32	0.36
Human-System	0.41	0.34	0.37
Manually harvested	0.46	0.41	0.43
Web-harvested	0.56	0.45	0.50

PortDial: Bottom-up Grammar Induction

- Goal: induction of high-level rules
  - Based on the availability of low-level rules
- Minimal set of examples (seeds) are provided
  - Analogous to the manual process of grammar development
  - Examples are automatically augmented
- Two sub-problems
  1. Extraction of fragments from corpus
     - Retain fragments with appropriate boundaries
     - E.g., “to depart from <City> on” VS “depart from <City>”
  2. Similarity between seeds and extracted fragments
     - Retain semantically similar fragments
     - E.g., “out of <City>” VS “to <City>”

PortDial: Bottom-up Grammar Induction



PortDial: Bottom-up Grammar Induction

1. Extraction of fragments
   - Binary classification problem
     - Valid / non-valid fragments
     - Seeds considered as valid fragments
   - Types of features
     - Lexical, e.g., frequency in corpus, num. of tokens
     - Syntactic, e.g., fragment perplexity, PoS info.
     - Semantic, e.g., similarity wrt to seeds
2. Similarity computation
   - Non-compositional: fragments as entire chunks
     - Various well-known lexical metrics
     - E.g., longest common sub-string similarity
   - Compositional: function of constituents' semantics
     - Recent open research problem
     - Models proposed for sentences, but not for phrases

PortDial: Bottom-up Grammar Induction

- Evaluation
  - Travel domain
  - Input: n seeds for each rule
    - $n < 5$
  - Output: m fragments suggested for each rule
    - m: user-defined
- Accuracy
  - Valid / non-valid fragments classification: 43%
  - Suggestion of semantically similar fragments: 30%
- However, in practice
  - Some non-valid fragments may be useful
    - Lengthier, e.g., “depart from <City> on”
  - Human-in-the-loop idea
    - Post corrections
    - Iterative process

PortDial: Bottom-up & Top-down Grammar Induction

- Goal: Fuse different approaches for grammar induction
  - High-level rules
- Approaches
  1. Bottom-up: corpus-based
  2. Top-down: based on ontology lexica
- Bottom-up (BU)
  - Relies on given seeds for each grammar rule
  - Extraction and suggestion of similar textual fragments
- Top-down (TD)
  - Ontology lexica: lexicalizations of ontological knowledge
  - Represent domain semantics in ontological representation
  - Possible lexicalizations are encoded as grammar rules

PortDial: Bottom-up & Top-down Grammar Induction

- Three fusion approaches
  1. Early fusion
     - Rules of TD triggered to generate a corpus; input to BU
  2. Mid fusion
     - TD grammar rules given as seeds to BU
  3. Late fusion
     - Rules of TD and BU are combined (union)
- Evaluation: Travel domain

Approach	Precision	Recall	F-measure
Bottom-Up (BU)	0.65	0.44	0.52
Top-Down (TD)	0.81	0.18	0.30
Early fusion	0.64	0.44	0.52
Mid fusion	0.56	0.54	0.55
Late fusion	0.72	0.55	0.63

SpeDial Objectives

- Devise machine-aided algorithms for spoken dialogue system enhancement and customization for call-center applications
- Create a platform that supports cost-effective service doctoring for
  - Service enhancement: the developer starts from an existing application and tries to improve performance and user satisfaction,
  - Service customization: the developer addresses the special needs of a user population
- Create and support a sustainable pool of developers that will be trained to use the platform

SpeDial: Multimodal Analytics for IVR

- Affective analysis of dialogues
  - Valence, arousal, mood, certain/uncertain
  - Also: gender, age, nativeness identification
- Call-flow, discourse and cross-modal analytics
  - Identify problematic and successful parts of the dialogues
  - Identify dialogue hot-spots
- Multilingual analytics
  - How previous sub-tasks can be applied across multiple languages

SpeDial: Enhancement and Customization

- Prompt and grammar enhancement
  - Select most appropriate prompts from the pool of prompts
  - Use transcriptions to train/update statistical grammars
  - Update FSM grammars via grammar induction
- Dialogue flow enhancement
  - Adjustment of system policies for successful interactions
- User modeling: prompt selection wrt
  - Age, gender, age & gender
- Multilinguality
  - SMT & crowd-sourcing to improve on prompts & grammars
  - Corpus-based methods for statistical grammar training
  - Direct translation of service grammars

SemEval'14: Task on Grammar Induction

- SemEval workshops
  - Various shared evaluations tasks of computational semantic analysis systems
  - SemEval'14: the 8th workshop
  - Co-located with COLING'14, Dublin, Ireland, August 2014
- SemEval'14 - Task 2
  - "Grammar induction for spoken dialogue systems"
  - Fosters the application of models of lexical semantics to spoken dialogue systems
  - Organized by the consortium of PortDial project

SemEval'14: Task on Grammar Induction

- Grammar rules distinguished into
  1. Low-level
     - Refer to basic concepts; comprised by lexical items only
     - E.g., <City> = ("New York", "London", ...)
  2. High-level
     - Grouping of semantically related textual fragments
     - Composed of both lexical items and low-level rules
     - E.g., <ArrivalCity> = ("fly to <City>", "arrive at <City>", ...)
- Parsing example
  1. "I want to fly to London"
  2. "I want to fly to <City>"
  3. "I want to <ArrivalCity>"

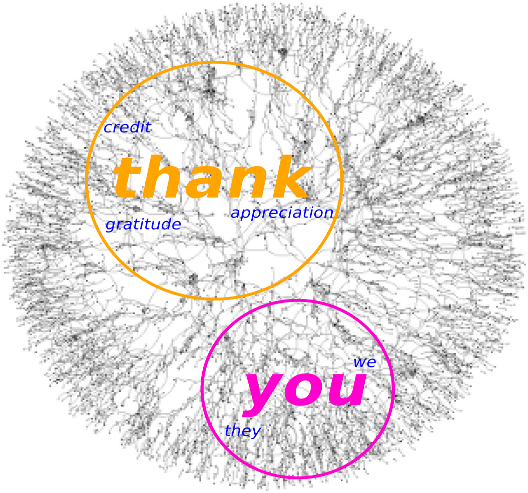
SemEval'14: Task on Grammar Induction

- Sub-problems
  1. Induction of low-level rules
     1. Well-investigated
     2. Also, use of resources, e.g., gazetteers
  2. Induction of high-level rules
     1. Segmentation problem: identify candidate fragments
     2. Similarity problem: compute similarity between fragments
- SemEval'14-Task 2
  - Focus on high-level rules
    - Low-level rules are given
  - Segmentation problem simplified as:
    - Discriminate between valid / non-valid fragments
  - Main focus: computation of similarity between fragments

SemEval'14: Task on Grammar Induction

- Train data
  - List of fragments for each grammar rule
  - Instances of low-level rules: given
  - List of non-valid fragments
- Test data
  - List of unknown fragments
  - For each unknown fragment:
    1. Is it a valid fragment?
    2. If so, assign it to the most similar rule

Domain	Language
Travel	English
Travel	Greek
Tourism	English
Finance	English


credit
thank
gratitude
appreciation
we
you
they