Automatic Detection and Classification of Social Events

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Overall Goal

Extract a social network from text where nodes are people and links are *social events*

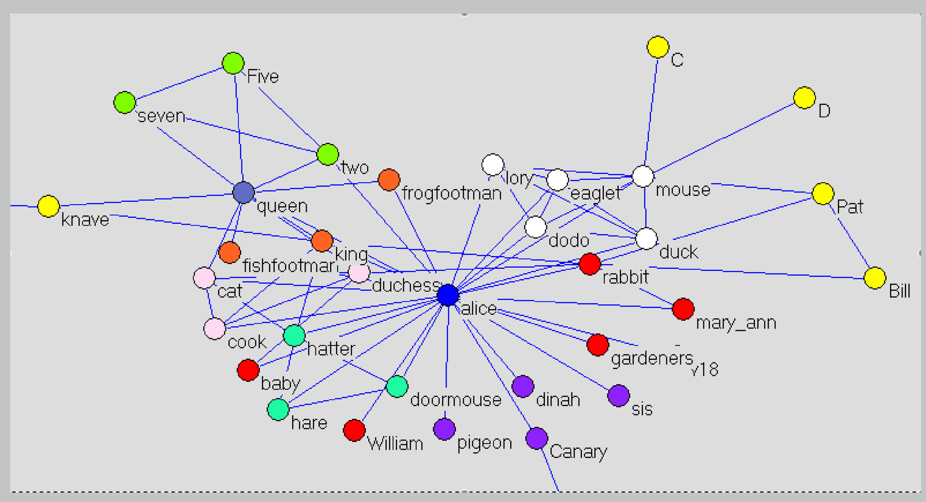


Figure: Social structure of *Alice in Wonderland*

Social Events (NEW)

Social Event:(Agarwal et. al. 2010) An event between two people or group of people where at least one party is aware of the other party and aware of the event. Types:

- Interaction event (INR): both parties mutually aware
- Cognition event (COG): only one party aware of the other

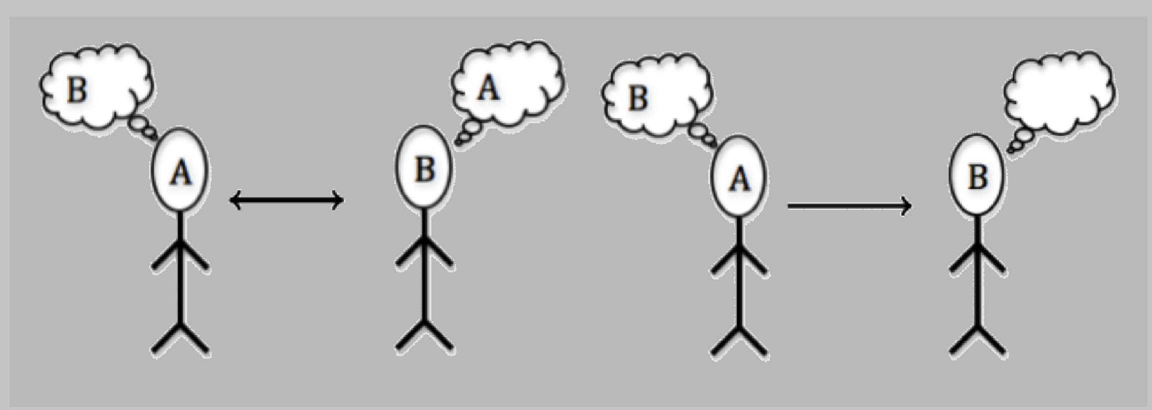
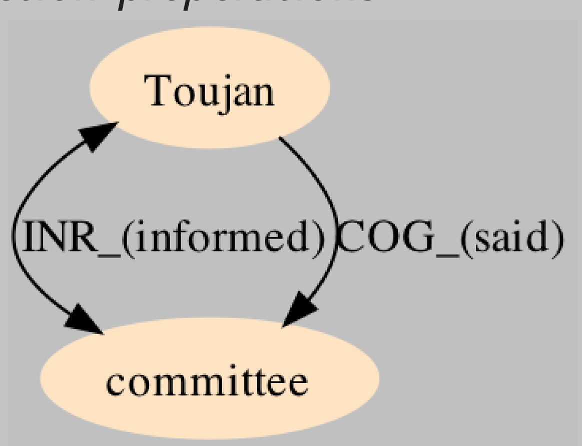


Figure: Interaction (INR) and Cognition (COG) social events respectively

Data

- We annotated social events for part of Automatic Content Extraction (ACE) data
- ACE already has annotations for entities, relations and events but:
  - Our definition of social event is conceptually different from ACE since we require reasoning about coginitive states of people
  - *[Toujan Faisal], 54, {said} [she] was {informed} of the refusal by an [Interior Ministry committee] overseeing election preperations*



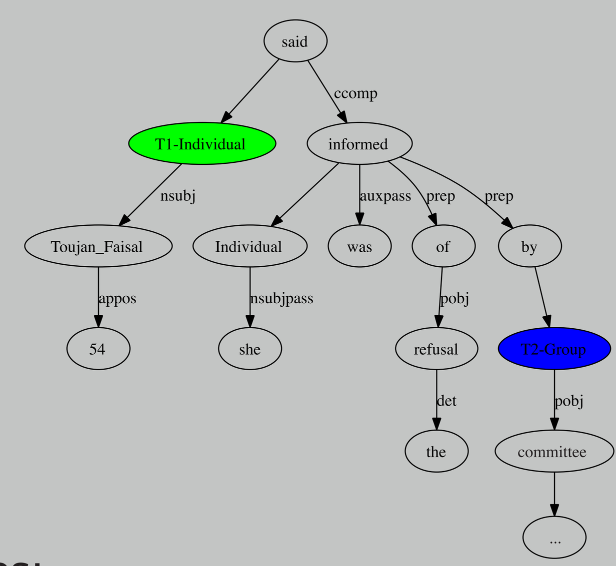
Data Sampling

- Under-sampling: Randomly eliminate examples of majority class until number of majority class examples equal number of minority class examples
- Over-sampling: Randomly duplicate minority class examples until number of minority class examples equal number of majority class examples
- Over-sampling with transformations: Generate synthetic minority class examples by "perturbing" the training data. Transformation used: (1) move the second target to its grandmother node, attaching it on the left, and recalculating the path-enclosed tree (2) repeate iteratively, so that a sentence with a deeply embedded second target yeilds a large number of synthesized examples

Task Definition

- Social Event Detection: Identifying if a pair of entities participate in some social event
- Social Event Classification: Given there is an event between two entities, Identifying weather it is an INR or COG event

Discrete Structures and Convolution Kernels



- Tree structures:
  - Phrase Structure Tree (PET)
  - Dependency Word Tree (DW)
  - Dependency Grammatical Relation Tree (GR)
  - Dependency Grammatical Relation Word Tree (GRW)
- Sequence structures:
  - SK1: *T1-Individual Toujan_Faisal 54 said Individual she was informed of the refusal by an T2-Group Interior Ministry committee*
  - SqGRW (NEW): *Toujan_Faisal nsubj T1-Individual said ccomp informed prep by T2-Group pobj committee*
- Kernels:
  - Subset Tree (SST): used for PET
  - Partial Tree (PT): used for all other structures

Except SqGRW, all the above structures and PT are due to work by Alessandro Moschitti and Vien Nguyen

Experiments and Results

Experimental Set-up:

- 138 ACE documents: 172 INR, 174 COG, 1291 No relation classes
- SVM with kernels: 5-fold cross-validation

Kernel	Event Detection (% F1)				Classification
	Baseline	Under	Over	Over+	% Acc
PET	32.4	41.9	53.6	47.3	76.8
GR	25.5	47.4	52.6	51.3	71.0
GRW	14.8	43.6	53.3	53.5	76.2
SqGRW	10.4	48.6	53.5	53.2	75.8
PET_GR	38.9	48.5	60.6	54.7	76.3
PET_GR_SqGRW	38.0	48.5	**61.1**	55.7	**78.7**
GR_SqGRW	36.2	47.3	54.5	54.0	75.6
GRW_SqGRW	25.0	47.1	54.1	55.3	76.9
GR_GRW_SqGRW	32.6	46.8	56.5	55.7	77.3

- Over-sampling performs best
- SqGRW plays role in both the best performing systems
- Combination of PST and DT works best
- Negative result: oversampling using transformations performed worse than oevrsampling

Conclusion and Future Work

- Introduced a new kernel (SqGRW)
- System pretty good at a seemingly difficult task of differentiating b/w INR and COG
- In future, incorporate semantic resources like VerbNet
- Try new linguistically motivated transformations

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