Mining Social Relationships from Text

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Overview: Studies of Increasing Complexity

What can we understand from text about social relationships?

- Contracts: Crisply stated relationships
  - Prescribed normative relationships
  - Commonly occurring exception conditions
  - Events and temporal relationships
- Corporate email and tech support chat: Vague relationships but with a directed purpose
  - Commitments
  - How they are delegated
  - How they are discharged
- Public social media: More implicit indications
  - Sentiment
  - How can we build a domain-specific lexicon?
  - *Ongoing Study:* Location
  - *Ongoing Study:* Influence

Contracts: Extracting Normative Relationships

- Classify each sentence occurring in a contract as a
  - Dialectical commitment, practical commitment, authorization, prohibition, sanction, power, or not a norm
- Norms that do not correspond 1-1 with sentences
- Approach
  - Surface patterns
  - Semantic classes
  - Heuristics
  - Machine learning

Key Textual Features with Examples

Subject contains organization name	Motorola; Google
Clause signal	if; unless
Modal verb	may; should
Negation present	not; neither
Only present	only
Main verb expresses an event	deliver; perform
Main verb expresses a state	have; be
Main verb has physical consequence	produce; pay
Main verb has social consequence	terminate; approve
Practical commitment signal	agree to
Dialectical commitment signal	it warrants; it is understood that
Authorization signal	shall have the right to ⟨physical⟩
Prohibition signal	must not
Power signal	shall have the right to ⟨social⟩
Sanction signal	responsible for any breach

Experimental Setting

- Gold standard
  - Selected 1,000 sentences from real-life contracts
  - Remove 38 sentences longer than 80 words each (often broken) to reduce noise and processing overhead
  - Remove 94 duplicate sentences
  - 868 sentences left after cleansing
  - Manually annotate each sentence with its norm type
- Features
  - Manually selected and automatically extracted
- Classification methods
  - Support Vector Machine (SVM)
  - Logistic regression (LR)
  - Naïve Bayes (NB)
- Evaluation
  - Ten-fold cross validation
  - Test on fresh data with model built from gold standard

Extraction Results (Ten-Fold Cross Validation)

Class	**LR**			**SVM**			**NB**		
	P	R	F	P	R	F	P	R	F
Practical C	0.87	0.80	0.83	0.88	0.70	0.78	0.83	0.81	0.82
Dialectical C	0.75	0.79	0.77	0.67	0.84	0.74	0.69	0.83	0.76
Authorization	0.67	0.69	0.68	0.68	0.65	0.66	0.65	0.76	0.70
Prohibition	0.64	0.68	0.66	0.64	0.61	0.63	0.68	0.59	0.63
Power	0.74	0.78	0.76	0.69	0.76	0.72	0.78	0.66	0.72
Sanction	0.43	0.25	0.32	–	–	–	–	–	–
Not a norm	0.58	0.47	0.52	0.42	0.33	0.37	0.60	0.20	0.30
Average	*0.75*	*0.74*	*0.74*	*0.71*	*0.71*	*0.71*	*0.72*	*0.73*	*0.72*

Determining Commitment Operations from Text

Commitments being the most prominent normative relationship

S	**R**	**Content**	**Operation**	$\mathbf{T}_{S,R}$	$\mathbf{T}_{R,S}$
Kim	*Dorothy*	I will also check with Alliance Travel Agency . . .	create(C_1)		
Kim	*Dorothy*	I checked with our Travel Agency . . .	discharge(C_1)		$\uparrow$
Rob	*Kim*	By Wednesday Aug 16 2001, please send all copies of your documentation . . .	create(C_2)		
Kim	*Rob*	Rob, please forgive me for not sending this in by Aug 15	cancel(C_2)		$\downarrow$

Identifying Commitment Operations from Interactions

Ten-fold cross-validation using SVM on marked up Enron email sentences

Commitment Operation	**P**	**R**	**F**	**Count**
Commissive create	0.87	0.97	0.92	342
Directive create	0.94	0.97	0.95	162
Delegate	0.86	0.33	0.48	12
Discharge	1.00	0.02	0.04	38
Cancel	–	–	–	7
None	0.98	0.98	0.98	3,540
Total				4,101

Features include

1. Modal verb (shall, will, may, might, can, could, would, must)
2. Type of subject (first person, second person, third person)
3. Tense
4. Deadline

Results

Ten-fold cross-validation using SVM on marked up chat sentences from HP IT corpus

Commitment Operation	Precision	Recall	F-measure
Commissive create	0.79	0.85	0.82
Directive create	0.73	0.85	0.83
Subcontract	–	–	–
Discharge	0.64	0.70	0.67
Cancel	0.22	0.13	0.16
None	0.97	0.97	0.97

The Concept of Sentiment Flow

- Sentiment changes across the text
- Opinion expressed in a clause is correlated with its neighboring clauses
- Sentiment flow can be used for inferring the fine-grained sentiment

Review: #233

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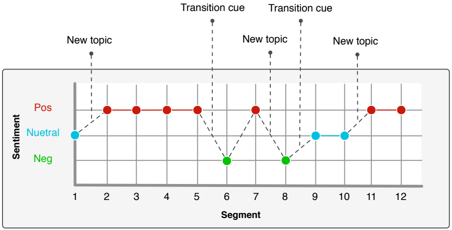
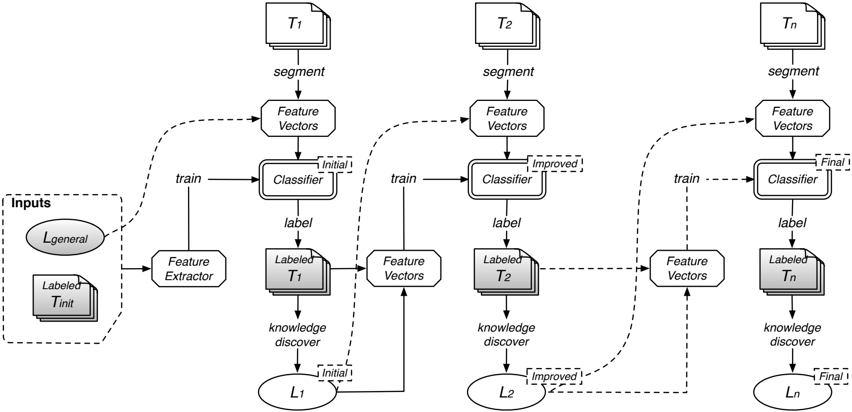
1. {We stayed here for one night before leaving on a cruise out of the San Pedro port. } **2.** {The hotel was clean and comfortable. } **3.** {Service was friendly} **4.** {, even providing us a late-morning check-in. } **5.** {The room was quiet and comfortable, } **6.** {but it was beginning to show a few small signs of wear and tear. } **7.** {The pool area was well-kept with plenty of fresh towels and lounge chairs available. } **8.** {Room service breakfast was subpar even for a three-star hotel} **9.** {, so skip that in favor of Think Cafe just up the street and around the corner. } **10.** {There are many local shops and restaurants in the neighborhood around the hotel if you're willing to walk a few blocks and explore. } **11.** {The free shuttle service to the cruise terminal is also a nice perk. } **12.** {All in all, a solid choice for a stay of just a night or two.}



The ReNew framework schematically



Feature Extraction

- **Grammar**: part-of-speech tag, the type of phrases or clauses
- **Opinion word**: positive or negative words
- **Dependency path**: "acomp" (adjectival complement), "amod" (adjectival modifier), and "nsubj" (nominal subject)
- **Punctuation and emoticon**
- **Transition cue**

Transition Types	**Examples**
Agreement/Addition/Similarity	also, similarly, as well as, ...
Opposition/Limitation/Contradiction	but, although, in contrast, ...
Cause/Condition/Purpose	if, since, as/so long as, ...
Examples/Support/Emphasis	including, especially, such as, ...

Knowledge Discovery

- Stanford typed dependencies as the basic unit in ReNew's lexicon
  - A grammatical relation holding between two words (head and dependent)
- Three typed dependencies used in current ReNew
  - amod: adjectival modifier

    e.g., "Great hotel,friendly helpful staff."

    $\hookrightarrow$ *amod (hotel, Great)*

    $\hookrightarrow$ *amod (staff, friendly)*

    $\hookrightarrow$ *amod (staff, helpful)*
  - acomp: adjectival complement

    e.g., "Pool looked nice especially at night."

    $\hookrightarrow$ *acomp (looked, nice)*
  - nsubj: nominal subject

    e.g., "The hotel and staff were perfect."

    $\hookrightarrow$ *nsubj (perfect, hotel)*

    $\hookrightarrow$ *nsubj (perfect, staff)*
- Extract the most frequent triples for each sentiment

Preliminary Results

Dataset

- A hotel review data set crawled from Tripadvisor
- Reviews with overall and aspect ratings regarding 818 hotels from seven U.S. cities
- 4,017 reviews from 340 users

Ground-Truth Labels

- Six annotators in two groups of three
- Label 200 reviews (2,424 segments) as positive, neutral, or negative
- A sentiment flow labeling toolkit called ReNew
- Fleiss' kappa score: 0.70 and 0.68

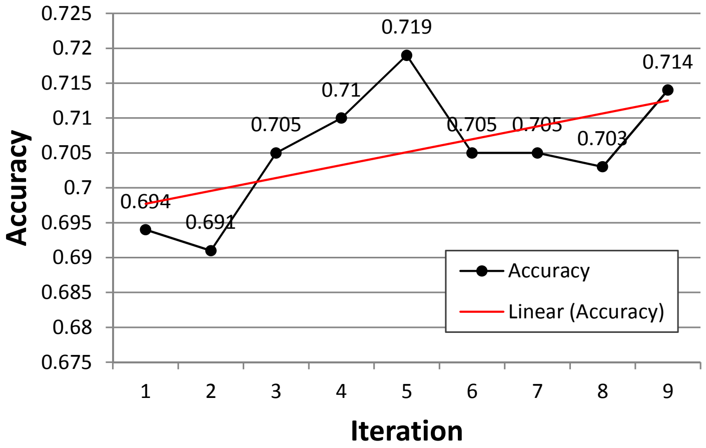
Preliminary Results

Sentiment Classification

- Goal: evaluate ReNew's self-learning feature
- For the first iteration
  - Training dataset: 100 labeled reviews
  - General sentiment lexicon: Linguistic Inquiry and Word Count (LIWC)
  - Train the initial classification model
- For each iteration thereafter
  - Analyze 200 unlabeled reviews randomly selected from our dataset
  - Discover knowledge
  - Retrain the classification model
  - Evaluate the accuracy of the model using the testing dataset

Preliminary Results

Classification accuracy over the number of iterations



Customized Lexicon Learned (Partial)

	amod-positive
Hotel	other nice great new mani good best larg favorit excel
Room	nice clean larg live standard separ comfort other great upgrad
Bed	comfort doubl comfi great clean nice new super good rollawai
	amod-negative
Room	new small upgrad live tini non-smok delux onli mani extra
Desk	front small other grouch welcom onsight onlin check-in oval
Servic	quick internet terribl overal turn-down poor person small call amen
	acomp-positive
Looks	nice good great dirti old date clean pretti fine cool
Feel	comfort welcom safe modern free gener sad dirti good cramp
Work	great fine hard perfect med better reliabl excel high low
Smell	good fresh nice great better strang amaz wonder excel weird
	acomp-negative
Looks	nice old ridicul crazi worn dirti tire
Felt	safe awkward roomi indiffer worn-out bad vulner under-serv modern
Mean	old okai easi horribl tini
	nsubj-positive
Bed	comfort comfi wa good #exclam clean great is nice amaz
Locat	great good perfect conveni excel beat fantast #colon best superb
Room	clean had nice comfort larg spaciou have quiet wa readi
Staff	friendli help nice great pleasant effici welcom accommod profession excel
	nsubj-negative
Servic	slow better #colon spotti shine effici avail bad start
Bathroom	small ha compact wa need #colon larg equip had
Bed	firm uncomfort look small need nice wa low
Room	small wa readi face avail quiet larg smell

Preliminary Results

Customized Lexicon Assessment

- Goal: evaluate the quality of the lexicon generated by ReNew
- Sentiment classification (positive, neutral, or negative)
- Dataset: 200 labeled reviews (2,424 segments)
- Features extracted from lexicons themselves
- Logistic regression in Weka
- Compare ReNew with two common sentiment lexicons
  - Affective Norms for English Words (ANEW)
  - LIWC

Preliminary Results

Comparison results of different lexicons.

	ANEW			**LIWC**			ReNew		
	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Precision	Recall	F-Measure
Positive	0.589	**0.987**	0.738	0.601	0.975	0.743	**0.641**	0.925	**0.757**
Negative	0.49	0.046	0.084	0.581	0.137	0.222	**0.564**	**0.193**	**0.287**
Neutral	0	0	0	0	0	0	**0.497**	**0.206**	**0.291**
Weighted average	0.451	0.587	0.45	0.477	0.6	0.483	**0.596**	**0.624**	**0.563**

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