Learning Compression & Linguistic Quality

Ling 573
Systems and Applications
May 12, 2016

Roadmap

- Sentence Compression:
  - Learning compression: Tree-based approach
  - Results & Discussion
- Linguistic Quality:
  - Corpus study and analysis
  - Automatic evaluation
  - Improvements for MDS

Learning Compression

- Cornell (Wang et al, 2013)

- Contrasted three main compression strategies
  - Rule-based
  - Sequence-based learning
  - Tree-based, learned models
- Resulting sentences selected by SVR model

Compression Corpus

- (Clark & Lapata, 2008)
- Manually created corpus:
  - Written: 82 newswire articles (BNC, ANT)
  - Spoken: 50 stories from HUB-5 broadcast news
- Annotators created compression sentence by sentence
  - Could mark as not compressable
- http://jamesclarke.net/research/resources/

Sequence-based Compression

- View as sequence labeling problem
  - Decision for each word in sentence: keep vs delete
  - Model: linear-chain CRF
    - Labels: B-retain, I-retain, O (token to be removed)
  - Features:
    - “Basic” features: word-based
    - Rule-based features: if fire, force to O
    - Dependency tree features: Relations, depth
    - Syntactic tree features: POS, labels, head, chunk
    - Semantic features: predicate, SRL
      - Include features for neighbors

Feature Set

- Detail:

Basic Features	Syntactic Tree Features
first 1/3/5 tokens (toks)?	POS tag
last 1/3/5 toks?	parent/grandparent label
first letter/all letters capitalized?	leftmost child of parent?
is negation?	second leftmost child of parent?
is stopword?	is headword?
Dependency Tree Features	in NP/VP/ADVP/ADJP chunk?
dependency relation (dep rel)	**Semantic Features**
parent/grandparent dep rel	is a predicate?
is the root?	semantic role label
has a depth larger than 3/5?	

Rule-Based Features
For each rule in Table 2 , we construct a corresponding feature to indicate whether the token is identified by the rule.

Tree-based Compression

- Given a phrase-structure parse tree,
  - Determine if each node is: removed, retained, or partial
- Issues & Solutions:
  - # possible compressions exponential
    - Order parse tree nodes (here post-order)
    - Do beam search over candidate labelings
  - Need some local way of scoring a node
    - Use MaxEnt to compute probability of label
  - Need some way of ensuring consistency
    - Restrict candidate labels based on context
  - Need to ensure grammaticality
    - Rerank resulting sentences using n-gram LM

Features

- Basic features:
  - Analogous to those for sequence labeling
- Enhancements:
  - Context features: decisions about child, sibling nodes
  - Head-driven search:
    - Reorder so head nodes at each level checked first
      - Why? If head is dropped, shouldn't keep rest
      - Revise context features

Summarization Features

- (aka MULTI in paper)
- Calculated based on current decoded word sequence W
- Linear combination of:
  - Score under MaxEnt
  - Query relevance:
    - Proportion of overlapping words with query
  - Importance: Average sumbasic score over W
  - Language model probability
  - Redundancy: 1 --- proportion of words overlapping summ

Summarization Results

	DUC 2006			DUC 2007		
System	**C Rate**	**R-2**	**R-SU4**	**C Rate**	**R-2**	**R-SU4**
Best DUC system	–	9.56	15.53	–	12.62	17.90
Davis et al. (2012)	–	10.2	15.2	–	12.8	17.5
SVR	100%	7.78	13.02	100%	9.53	14.69
LambdaMART	100%	9.84	14.63	100%	12.34	15.62
Rule-based	78.99%	10.62 ∗†	15.73 †	78.11%	13.18†	18.15†
Sequence	76.34%	10.49 †	15.60 †	77.20%	13.25†	18.23†
Tree (BASIC + $Score_{Basic}$)	70.48%	10.49 †	15.86 †	69.27%	13.00†	18.29†
Tree (CONTEXT + $Score_{Basic}$)	65.21%	10.55 ∗†	16.10 †	63.44%	12.75	18.07†
Tree (HEAD + $Score_{Basic}$)	66.70%	10.66 ∗†	16.18 †	65.05%	12.93	18.15†
Tree (HEAD + MULTI)	70.20%	**11.02** ∗†	**16.25** †	73.40%	**13.49**†	**18.46**†

Compression Results

System	C Rate	Uni-Prec	Uni-Rec	Uni-F1	Rel-F1
HedgeTrimmer	57.64%	0.72	0.65	0.64	0.50
McDonald (2006)	70.95%	0.77	0.78	*0.77*	0.55
Martins and Smith (2009)	71.35%	0.77	0.78	*0.77*	0.56
Rule-based	87.65%	0.74	0.91	0.80	0.63
Sequence	70.79%	0.77	0.80	*0.76*	0.58
Tree (BASIC)	69.65%	0.77	0.79	0.75	0.56
Tree (CONTEXT)	67.01%	**0.79**	0.78	*0.76*	0.57
Tree (HEAD)	68.06%	**0.79**	0.80	*0.77*	**0.59**

Discussion

- Best system incorporates:
  - Tree structure
  - Machine learning
  - Summarization features
- Rule-based approach surprisingly competitive
  - Though less aggressive in terms of compression
- Learning based approaches enabled by sentence compression corpus

General Discussion

- Broad range of approaches:
  - Informed by similar linguistic constraints
  - Implemented in different ways:
    - Heuristic vs Learned
    - Surface patterns vs parse trees vs SRL
  - Even with linguistic constraints
    - Often negatively impact linguistic quality
    - Key issue: errors in linguistic analysis
      - POS taggers → Parsers → SRL, etc

Linguistic Quality

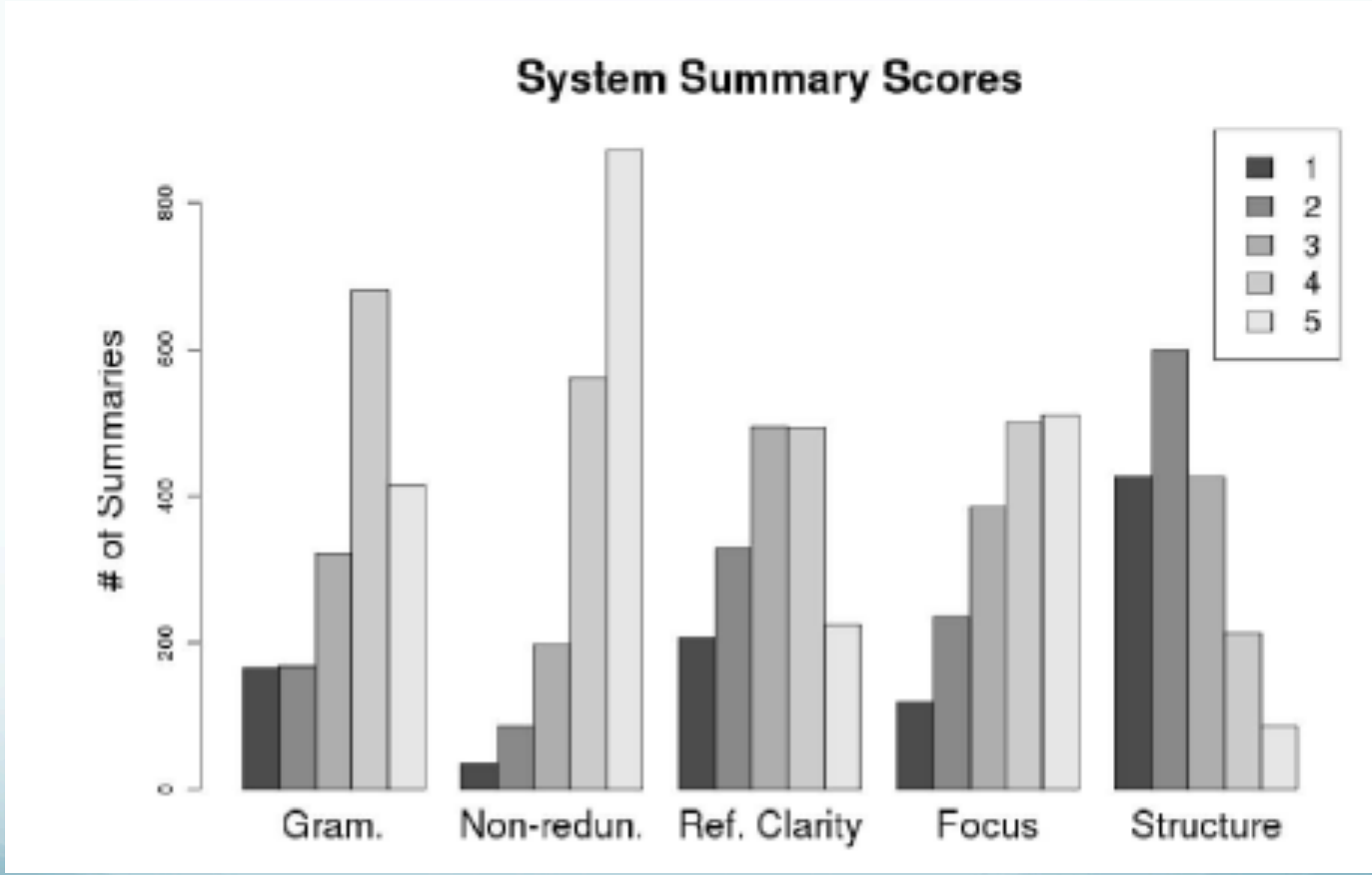
Evaluation

- Shared tasks:
  - Take content as primary evaluation measure
    - ROUGE, Pyramid, (manual) Responsiveness
  - Linguistic quality also part of formal evaluation
- TAC "Readability":
  - Scored manually on 5-point Likert scale
  - Aims to capture readability, fluency
    - Independent of summary content

What is “Readability”?

- According to TAC,
- Assessors consider (and rate 1-5) each of:
  - Grammaticality:
    - No fragments, datelines, ill-formed sentences, etc
  - Non-redundancy:
    - No unnecessary repetition: includes content, sentences, or full NPs when pronoun is better
  - Referential clarity:
    - Both presence/salience of antecedents, relevance of items
  - Focus:
    - Only content related to summary
  - Coherence: “Well-structured”

Score Distributions



What is “Readability”? II

- Definition subsumes many phenomena, errors
- What types of errors do these systems make?
- What errors, issues are reflected in the scores?
- LVQSumm (Friedrich et al, 2013)
  - Annotate linguistic “violations” in automatic summaries
    - TAC2011 data: ~2000 “peer” summaries
    - Categorize and tabulate
  - Assess correlation with Readability scores

Example

Charles Carl Roberts IV may have planned to molest the girls at the Amish school, but police have no evidence that he actually did. Charles Carl Roberts IV entered the West Nickel Mines Amish School in Lancaster County and shot 10 girls, killing five. The suspect apparently called his wife from a cell phone shortly before the shooting began, saying **he was "acting out in revenge for something that happened 20 years ago,** Miller said. The gunman, a local truck driver Charles Roberts, was apparently **acting in "revenge" for an incident that happened to him 20 years ago.**

Violation Categories

- Entity mentions:
  - Affect coreference and readability
  - 1st mention w/o explanation; subseq. Mention w/expl
  - Def NP w/o prev mention; indef NP w/ prev mention
  - Pron w/missing, misleading antecedent; Acronym
- Clausal level:
  - Arbitrary spans – up to sentence level
  - Incomplete sent, dateline info, other ungrammatical
  - No semantic relation, wrong discourse rel'n, redundancy

violation type	count	avg/doc	Pearson's r Readability	Pyramid	Respons.
entity level violations					
DNP-REF	958	0.50	**-0.122**	**-0.166**	**-0.133**
FM-EXPL	792	0.41	0.006	-0.050	**-0.066**
INP+REF	430	0.22	-0.052	**0.235**	**0.109**
PRN+MISSA	361	0.19	**-0.191**	**-0.140**	**-0.156**
SM+EXPL	162	0.08	0.020	**0.089**	0.045
PRN+MISLA	27	0.01	**-0.065**	**-0.073**	**-0.089**
ACR-EXPL	11	0.01	-0.038	-0.056	-0.006
sum(DNP-REF, PRN+MISSA)	1319	0.68	**-0.204**	**-0.208**	**-0.192**
sum(entity level violations)	2741	1.42	**-0.167**	-0.074	**-0.127**
clause level violations					
INCOMPLSN	1,044	0.54	**-0.210**	0.000	-0.029
OTHRUNGR	793	0.41	**-0.180**	0.007	-0.016
INCLDATE	412	0.21	**-0.090**	0.039	0.051
REDUNDINF	504	0.26	**-0.160**	**0.156**	**0.077**
NOSEMREL	142	0.07	**-0.148**	**-0.102**	**-0.132**
NODISREL	91	0.05	-0.025	**-0.081**	**-0.062**
misleading discourse connectives⋆	114	0.06	-	-	-
sum(clause level violations)	2,986	1.54	**-0.325**	0.041	-0.016
sum(clause level violations, DNP-REF, PRN+MISSA)	4,305	2.22	**-0.385**	**-0.084**	**-0.122**
sum(all violations)	5,727	2.96	**-0.356**	-0.022	**-0.101**

Further Analysis

- Linear model investigates the relationship of particular errors to readability

Feature	Weight	Feature	Weight
Intercept	3.407	DNP-REF	**-0.157**
ACR-EXPL	-0.361	OTHRUNGR	**-0.155**
PRN+MISLA	**-0.355**	INCLDATE	**-0.151**
INCOMPLSN	**-0.275**	INP+REF	-0.067
NOSEMREL	**-0.262**	NODISREL	-0.046
REDUNDINF	**-0.259**	FM-EXPL	-0.023
PRN+MISSA	**-0.236**	SM+EXPL	0.038

- Most significant factors: Missing/Misleading refs, fragments, redundant content, poor coherence

- Total # of errors well-correlated with system ranks

Automatic Evaluation of Linguistic Quality

- Motivation:
  - No focus on linguistic quality b/c no way to tune to it
  - Everyone uses ROUGE b/c you can tune
    - Explicitly tuned in many ML models
- Alternative strategies:
  - Micro: Learn to predict component scores
  - Macro: Learn to predict overall readability score
    - Intuitively: error count (LVQSumm) predicts well, but…
      - Errors manually derived

Micro-Quality Prediction

- (Pitler et al, 2010) via SVM ranking

- Evaluate multiple measures aimed to model LQ
  - General word choice, sequence: Language Models
  - Reference form:
    - Named Entities: modification for 1st mention of PER
    - NP syntax: POS, phrase tags in NPs
  - Local coherence
    - Devices: counts of pron, dem, connectives,...
    - Continuity: adjacency in source, coref w/prev, same, cosine
  - Sentence fluency: features from MT eval
  - Coh-Metrix: set of psycho-ling motivated feats, LSA sim
  - Word coherence: cross-sentence word cooccurrence patterns
  - Entity coherence: via Entity-grids (Brown toolkit)

Results

- System level
- Summary level

Feature set	Gram.	Redun.	Ref.	Focus	Struct.
Lang. models	87.6	83.0	91.2	85.2	86.3
Named ent.	78.5	83.6	82.1	74.0	69.6
NP syntax	85.0	83.8	87.0	76.6	79.2
Coh. devices	82.1	79.5	82.7	82.3	83.7
Continuity	88.8	**88.5**	**92.9**	**89.2**	**91.4**
Sent. fluency	**91.7**	78.9	87.6	82.3	84.9
Coh-Metrix	87.2	86.0	88.6	83.9	86.3
Word coh.	81.7	76.0	87.8	81.7	79.0
Entity coh.	90.2	88.1	89.6	85.0	87.1
Meta ranker	**92.9**	87.9	91.9	87.8	90.0

Feature set	Gram.	Redun.	Ref.	Focus	Struct.
Lang. models	66.3	57.6	62.2	60.5	62.5
Named ent.	52.9	54.4	60.0	54.1	52.5
NP Syntax	59.0	50.8	59.1	54.5	55.1
Coh. devices	56.8	54.4	55.2	52.7	53.6
Continuity	61.7	62.5	**69.7**	**65.4**	**70.4**
Sent. fluency	**69.4**	52.5	64.4	61.9	62.6
Coh-Metrix	65.5	**67.6**	67.9	63.0	62.4
Word coh.	54.7	55.5	53.3	53.2	53.7
Entity coh.	61.3	62.0	64.3	64.2	63.6
Meta ranker	**71.0**	**68.6**	**73.1**	**67.4**	**70.7**

Findings

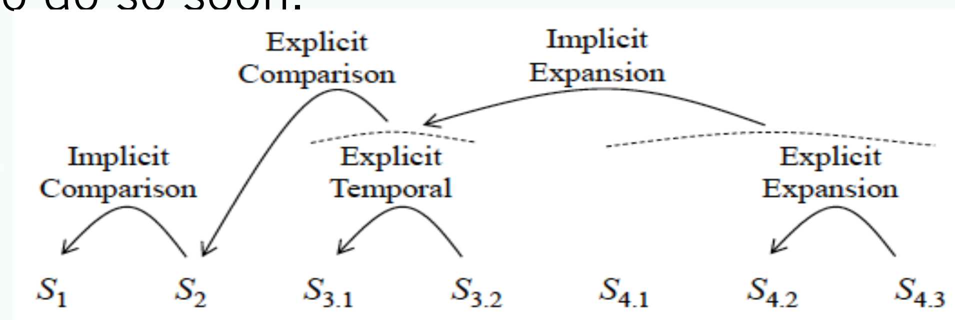
- Overall accuracies quite good
- Systems overall easier to rank than particular input
  - Smoothes variance, larger sample
- Continuity related features best across components
  - Ensemble of ordering, coref, cosine similarity cues
    - Though LSA-based system detects redundancy well
- Specifically tuned fluency scorer works on fluency

Macro-Quality Prediction

- (Lin et al, 2012) Downloadable

- High-level idea:
  - Discourse version of entity grid
    - Columns: entities (same head)
    - Rows: sentences
    - Cell values: PDTB Relation.Arg# tuples
- Variants:
  - Inter-cell sequence frequencies
    - + Additional tuples: {Non--}Explicit.Relation.Arg#
    - + Intra-cell "sequences"

S_1: Japan normally depends heavily on the Highland Valley and Cananea mines as well as the Bougainville mine in Papua New Guinea.
S_2: Recently Japan has been buying copper elsewhere.
$S_{3.1}$:But as Highland Valley and Cananea begin operating,
$S_{3.2}$: they are expected to resume their roles as Japan's suppliers.
$S_{4.1}$: According to Fred Demler, metals economist for DBL, New York,
$S_{4.2}$: "Highland Valley has already started operating
$S_{4.3}$: and Cananea is expected to do so soon."



S#	Copper	Cananea	operat	depend	..
S_1	Nil	Comp.A1	Nil	Comp.A1	
S_2	Comp.A2 Comp.A1	Nil	Nil	Nil	
S_3	Nil	Comp.A2 Temp.A1 Exp.A1	Comp.A2 Temp.A1 Exp.A1	nil	
S_4	Nil	Exp.A1	Exp.A1 Exp.A2	nil	

Results

- Very strong correlations w/manual readability score
  - Beats prior predictors

	Initial			Update		
	P	S	K	P	S	K
R-2	0.7524	0.3975	0.2925	0.6580	0.3732	0.2635
R-SU4	0.7840	0.3953	0.2925	0.6716	0.3627	0.2540
BE	0.7171	0.4091	0.2911	0.5455	0.2445	0.1622
4	0.8194	0.4937	0.3658	0.7423	0.4819	0.3612
6	0.7840	0.4070	0.3036	0.6830	0.4263	0.3141
12	0.7944	0.4973	0.3589	0.6443	0.3991	0.3062
18	0.7914	0.4746	0.3510	0.6698	0.3941	0.2856
23	0.7677	0.4341	0.3162	0.7054	0.4223	0.3014
LIN	**0.8556**	**0.6593**	**0.4953**	**0.7850**	**0.6671**	**0.5008**
LIN+C	**0.8612**	**0.6703**	**0.4984**	**0.7879**	**0.6828**	**0.5135**
LIN+E	**0.8619**	**0.6855**	**0.5079**	**0.7928**	**0.6990**	**0.5309**
DICOMER	**0.8666**	**0.7122**	**0.5348**	**0.8100**	**0.7145**	**0.5435**