Applications using WSD or SRL

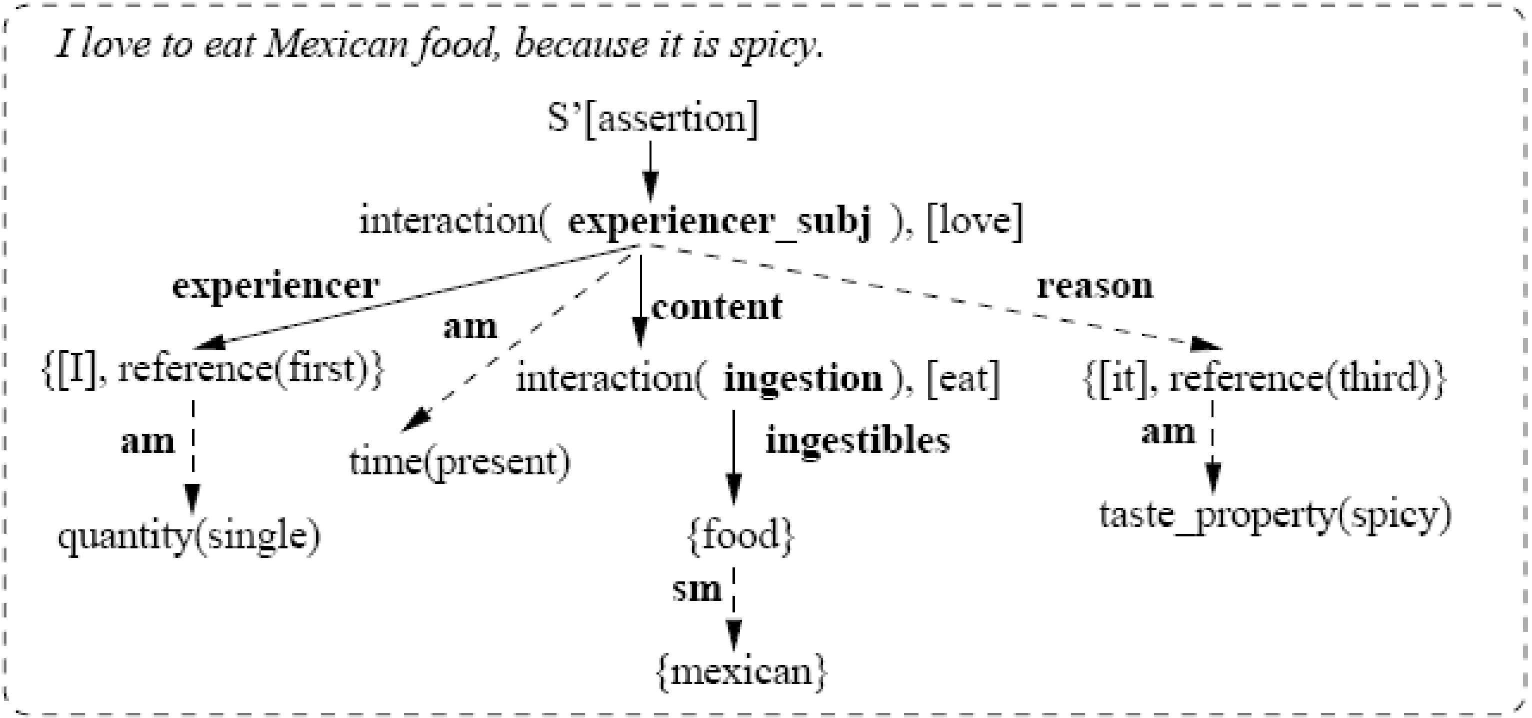
Expansion of a verb lexicon
(Swift, 2005)

- Spoken dialog system with defined lexicon
- Used VerbNet classes to discover new verbs
- Automatically generated representations for previously unknown verbs, with syntactic and semantic information

Knowledge base construction(Shi & Mihalcea, 2005)

- Expand VerbNet with FrameNet semantic roles
- Use VN selectional restrictions to connect to WN nouns
- (Verb, SenseID, Verb_Class, Frame)
- (Verb, SenseID, Role_With_Syntax_List)
- Uses syntax-semantic correspondences to derive semantic relations in a sentence and assign semantic roles.

Semantic parse tree
(Shi and Mihalcea, 2005)



Question answering

- Automatically answering a question posed in natural language
- Determine question type
  - Where is Los Alamos?
  - When did Obama become president?
  - Where is Columbus?
- Find possible question answers (IR)
- Filter answers
- Rank remaining answers to get the best one

Semantic role labeling

- Correspondence between roles in questions and answers

Who bombed the Justice Center in Chicago?

Agent Patient Location

Last week in Chicago's south side, John Lee

Time Location Agent

exploded a bus outside the Justice Center.

Patient

Ranking answers

- Moschitti et al. (2010) use question and answer pairs, judging question and answer similarity, based on syntactic parses and shallow semantic parses
- Depends on automatic PropBank semantic role labeling (Moschitti et al., 2005) to create shallow semantic parses
- End system improves bag-of-words approach by 63%

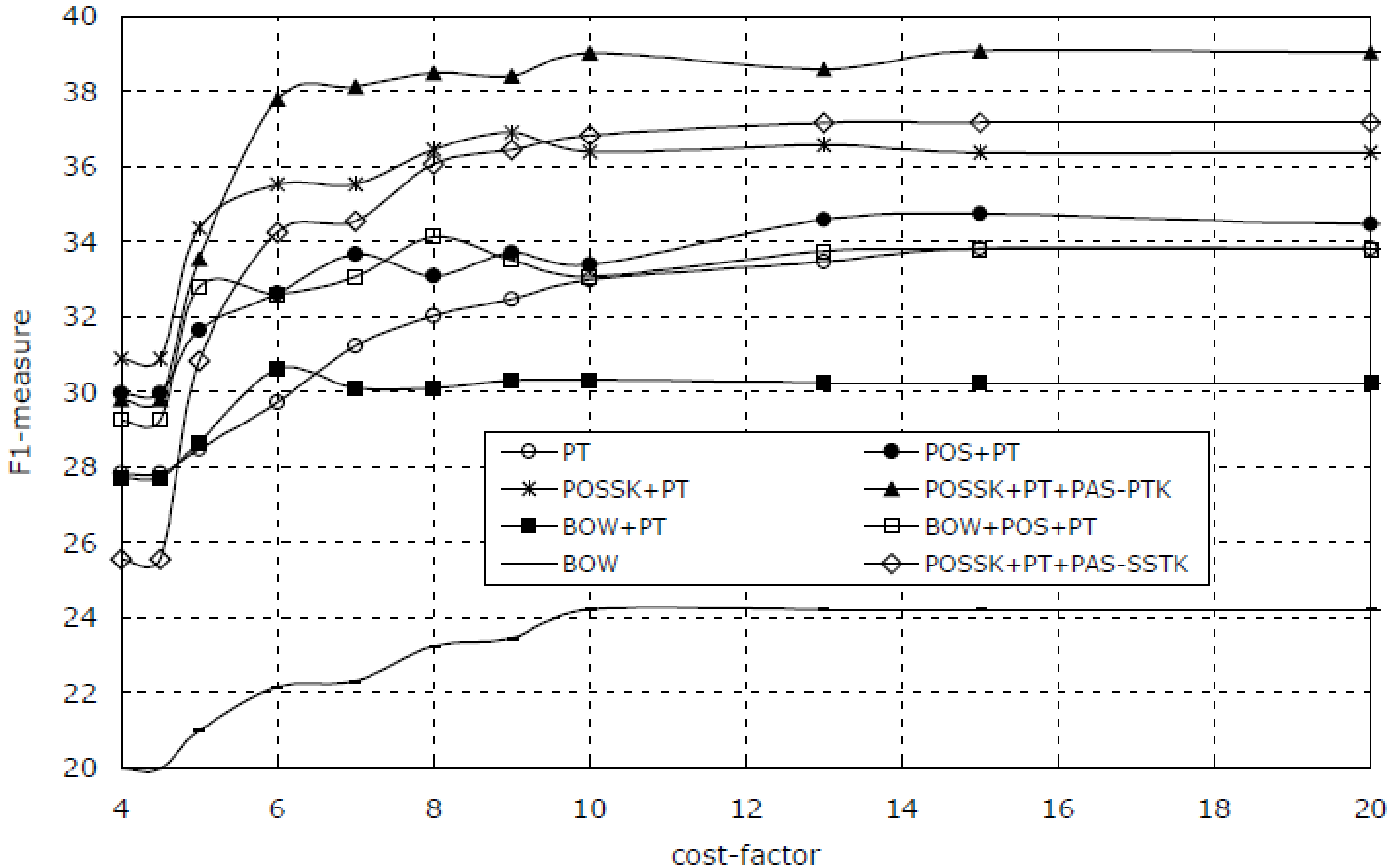


Figure 8: Impact of different feature sets on the TREC-QA dataset

Watson question answering

- IBM computer system designed to answer questions
- SRL with PropBank (??)
- Question categorization uses automatic PropBank labeling (Moschitti)

Parc and Powerset question answering system

- Rule-based system with some stochastic components maps English text to semantics/knowledge representation
- Use Sem/KR for improved search and question answering
  - word level: synonyms/hypernyms/aliases
  - structure level: canonicalization (e.g. passives mapped to actives, eventive nouns mapped to verbs), expansion (e.g. *kill* -> *die*, *buy* roles -> *sell* roles)
  - roles between relations and arguments are crucial: VerbNet

Goals for VerbNet roles

- Map syntax roles (subject, object, etc) into semantic, thematic roles via VerbNet mappings
- Requires
  - XLE syntax -> VerbNet subcat frame mappings
  - mappings for:
    - verbs not known to VerbNet
    - verb-subcat pairs not known to VerbNet
- Done via Unified Lexicon of information from
  - XLE syntactic and semantic lexicons
  - VerbNet
  - WordNet

Syntax:
PRED ‘break<SUBJ>’
SUBJ ‘window’
PASSIVE -

Semantics:
role(hier(sb,[[T,root]]), break:12, window:5)
lex_class(break:12,
  [vnclass(appear-48.1.1),
  vnclass(break-45.1),
  vnclass(hurt-40.8.3-1-1)])

Syntax:
PRED ‘break<SUBJ,OBJ>’
SUBJ ‘Mary’
OBJ ‘window’
PASSIVE -

Semantics:
role(hier(ob,[[T,root]]), break:6, window:16)
role(hier(sb,[[E,root],[I,E,root]]), break:6, mary:1)
lex_class(break:6,
  [vnclass(break-45.1),
  vnclass(cheat-10.6),
  vnclass(hurt-40.8.3-1-1)])

VerbNet event semantics

VN also provides an event semantics, which we tried to use to deduces change of location information. The general encoding format seemed to be very suited to this but the coverage is very incomplete. For instance:

class 9.3 (funnel), only endpoints are given

Funnel the liquid from the bottle into the cup.

class 9.5 (pour), no frame with both start and end points

He poured the water from the bowl into the cup

class 9.7

OK: Jessica loaded boxes into the wagon

Not: Jessica loaded the boxes from the train into the car.

10.2 (banish) and class 10.4.2 (shovel) both a source and a destination frame are given but no frame that combines the two.

Shovel the snow from the sidewalk into the ditch.

Parc question answering project: evaluation of VerbNet as a component

- Need a broad coverage resource mapping from surface realization (syntactic grammatical functions) to semantic (thematic) roles
- VerbNet provides base resource
  - improves default mappings for specific verb classes
- Issues with
  - coverage (missing verbs, frames)
  - interpretation and uniformity of roles and event semantics across frames

Parc q/a system

- Uses VN semantic predicates to derive pre- and post-event conditions, such as change of location

- **MOTION(**DURING(E), THEME**)**
  LOCATION(START(E), THEME, SOURCE**)**
  NOT(LOCATION(END(E), THEME, SOURCE**))**
  DIRECTION(DURING(E), FROM, THEME, SOURCE**)**
- To show the theme was in one location before the event and a different one afterward

Metaphorical extensions?

- We ignore the problem of metaphorical extensions for the relevant verbs. Resources other than VerbNet will need to be exploited to insure that these non-physical interpretations are excluded. (Bobrow et al., 2007)

The students left.	**Escape-51.1**	**MOTION(DURING(E), THEME) DIRECTION(DURING(E), PREP_DIR, THEME, ?OBLIQUE)**
Elvis has left the building.	leave-51.2	MOTION(DURING(E), THEME) LOCATION(START(E), THEME, SOURCE) NOT(LOCATION(END(E), THEME, SOURCE)) DIRECTION(DURING(E), FROM, THEME, SOURCE)
He left Microsoft in 2008.	resign-10.11	CAUSE(AGENT, E) LOCATION(START(E) SOURCE) NOT(LOCATION(END(E), SOURCE))
He left the tenant with his business card.	fulfilling-13.1.4	HAS_POSSESSION(START(E), AGENT, THEME) HAS_POSSESSION(END(E), RECIPIENT, THEME) TRANSFER(DURING(E), THEME) CAUSE(AGENT, E)
He left Sam his stamp collection.	future_having-13.3	HAS_POSSESSION(START(E), AGENT, THEME) FUTURE_POSSESSION(END(E) RECIPIENT, THEME) CAUSE(AGENT, E)
She left the papers in her desk	keep-15.2	PREP(DURING(E), THEME, LOCATION) CAUSE(AGENT, E)

Multiple senses of leave

- Only one fits their needs
- Most frequent class heuristic is 59% accurate
- Automatic VerbNet classifier (Brown et al., 2010)
- 89% accuracy
- Work with them to improve their system

Opinion mining/sentiment analysis

- Uses PropBank semantic role labeling as features

System	P	R	F
Baseline	63.36	46.77	53.82
Label pairs	62.05	52.68	56.98
All syntactic	62.45	53.19	57.45
All semantic	61.26	53.85	57.31
Syn + sem	61.02	55.67	58.22
Syn + sem + pairs	61.61	54.78	57.99

(Moschitti et al., 2010)

Machine translation English-Chinese

- Exploiting a parallel corpus with PropBank semantic role annotations (Palmer et al.)
- Great difficulty in word aligning these corpora
- Translation often leaves out key participants
- SRL can identify key components of the sentence so those at least have some translation

Machine translation English-Chinese

- Automatically label verbs with verbnet classifier (verb sense disambiguator)
- Using a parallel corpus, generate corresponding verb classes in Chinese
- If a verb doesn't occur in the training data, but appears in the test data
- Use the class for back-off

WSD applications missing

- Inconclusive results
- Some show improvement
- More don't
- Some show they hurt (e.g., information retrieval; Voorhees, 1999).
- Need high accuracy to help (Sanderson, 2000)
- Many of these applications used WordNet senses
- Results with different sense inventory?

SRL in applications

- Fairly new task
- Needed to improve to levels that might actually help another system
- Now starting see in end applications with promising results