Joint Models for Concept-to-Text Generation

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22 October 2013

Outline

1. **Grammar-based Generation**
   - Unsupervised Concept-to-text Generation w/ Hypergraphs, NAACL 2012
   - A Global Model for Concept-to-Text Generation, JAIR 2013, In press.
2. **Inducing Document Plans**
   - Inducing Document Plans for Concept-to-text Generation, ACL 2013
3. **Discriminative Reranking: An exploratory study**
   - Concept-to-text Generation via Discriminative Reranking, ACL 2012

Introduction

Concept-to-text generation refers to the task of automatically producing textual output from nonlinguistic input (Reiter and Dale, 2000)

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Wind Chill

Time	Min	Mean	Max
06-21	0	0	0

Temperature

Time	Min	Mean	Max
06-21	52	61	70

Wind Speed

Time	Min	Mean	Max
06-21	11	22	29

Wind Direction

Time	Mode
06-21	S

Gust

Time	Min	Mean	Max
06-21	0	20	39

Precipitation Potential

Time	Min	Mean	Max
06-21	26	81	100

Sky Cover

Time	Percent (%)
06-21	75-100
06-09	75-100
06-13	50-75
09-21	75-100
13-21	75-100

Rain Chance

Time	Mode
06-21	Def
06-09	Lkly
06-13	Def
09-21	Def
13-21	Def

Snow Chance

Time	Mode
06-21	–
06-09	–
06-13	–
09-21	–
13-21	–

Sleet Chance

Time	Mode
06-21	–
06-09	–
06-13	–
09-21	–
13-21	–

Freezing Rain Chance

Time	Mode
06-21	–
06-09	–
06-13	–
09-21	–
13-21	–

Thunder Chance

Time	Mode
06-21	Def
06-09	Lkly
06-13	Chc
09-21	Def
13-21	Def

Showers and thunderstorms. High near 70.

Cloudy, with a south wind around 20mph, with gusts as high as 40 mph.

Chance of precipitation is 100%.

Introduction

Concept-to-text generation refers to the task of automatically producing textual output from nonlinguistic input (Reiter and Dale, 2000)

Desktop

Cmd	Name	Type
left-click	start	button

Start

Cmd	Name	Type
left-click	settings	button

Location

Name	Type
start menu	button
control panel	window

Start Target

Cmd	Name	Type
left-click	control panel	button

Navigate Window

Cmd	Name	Type
left-click	accounts and users	window

Context Menu

Cmd	Name	Type
left-click	advanced	tab

Action Context Menu

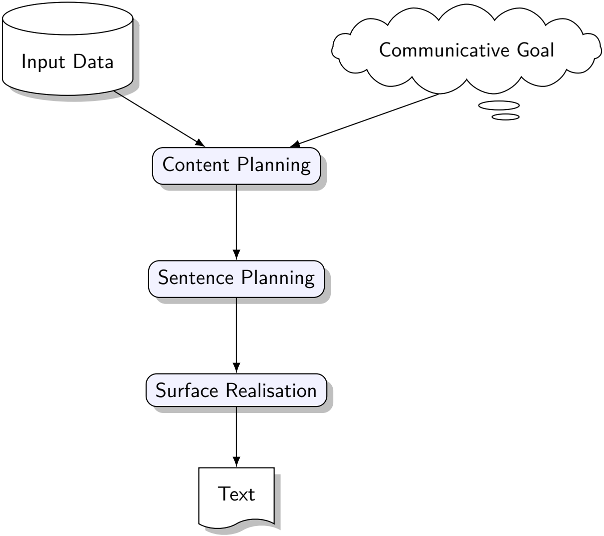
Cmd	Name	Type
left-click	advanced	button

Window Target

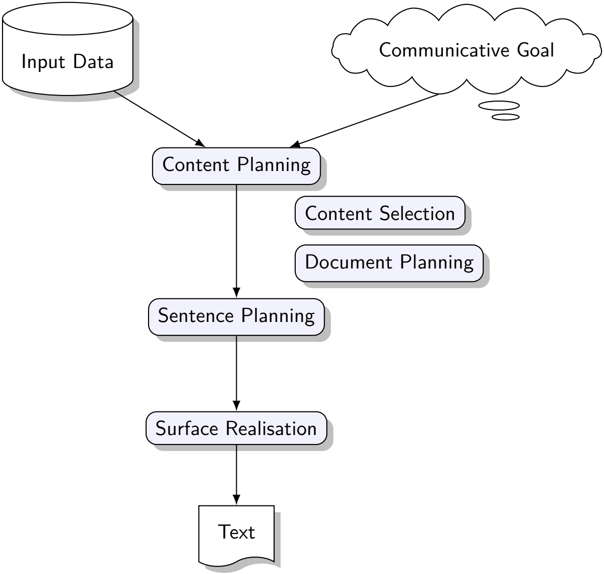
Cmd	Name	Type
double-click	users and passwords	item

Click start, point to settings, and then click control panel.
Double-click users and passwords.
On the advanced tab, click advanced.

Traditional NLG Pipeline



Traditional NLG Pipeline



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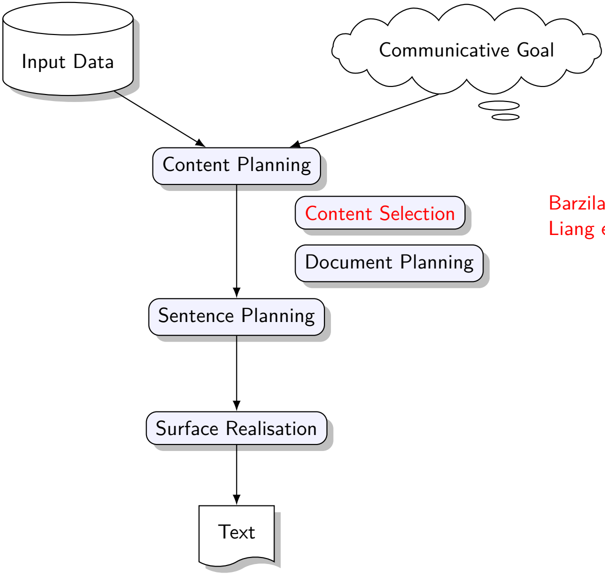

Barzilay and Lapata (2005)
Liang et al. (2009)

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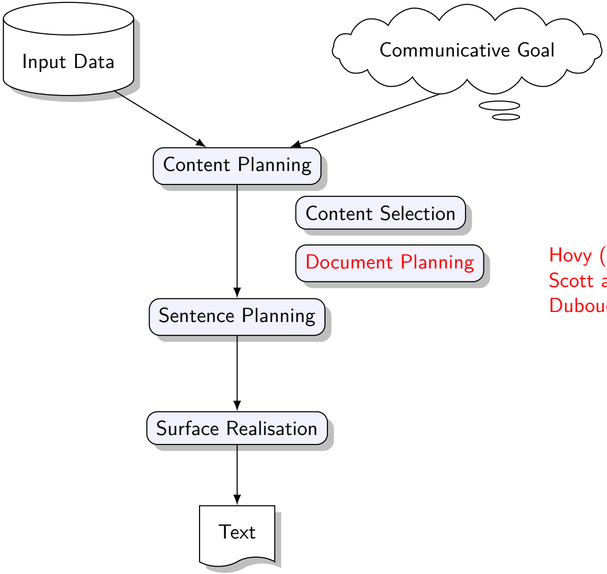

Hovy (1993)
Scott and de Souza (1990)
Duboue and Mckeown (2002)

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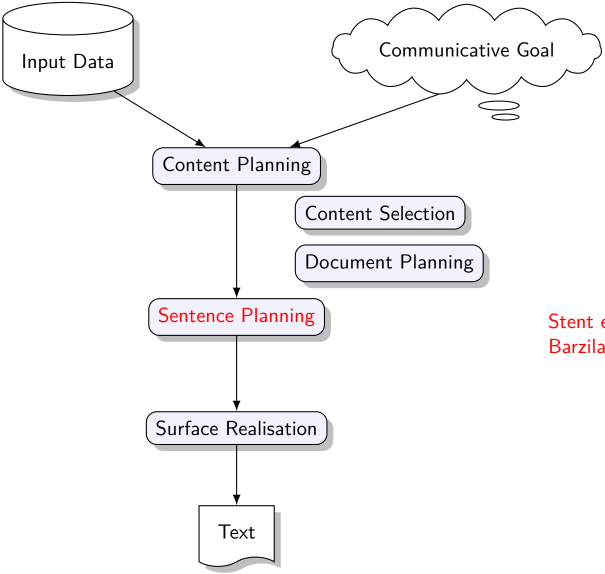

Stent et al. (2004)
Barzilay and Lapata (2006)

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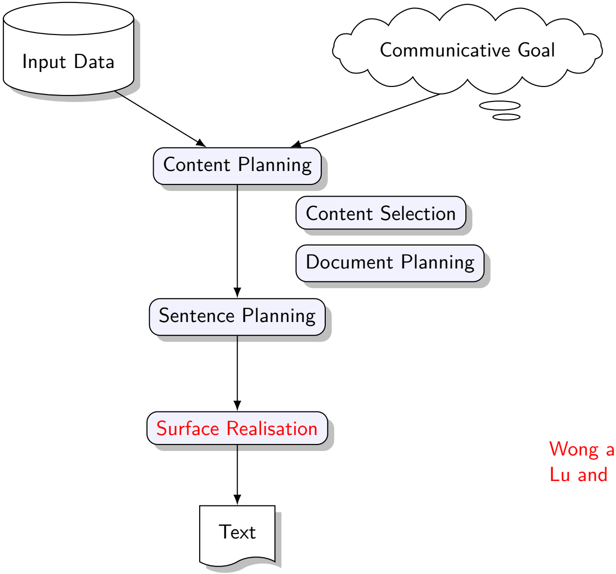

Wong and Mooney (2007)
Lu and Ng (2011)

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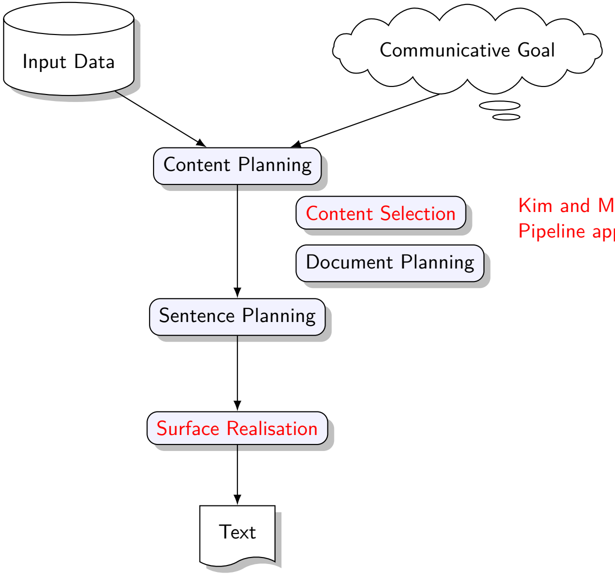
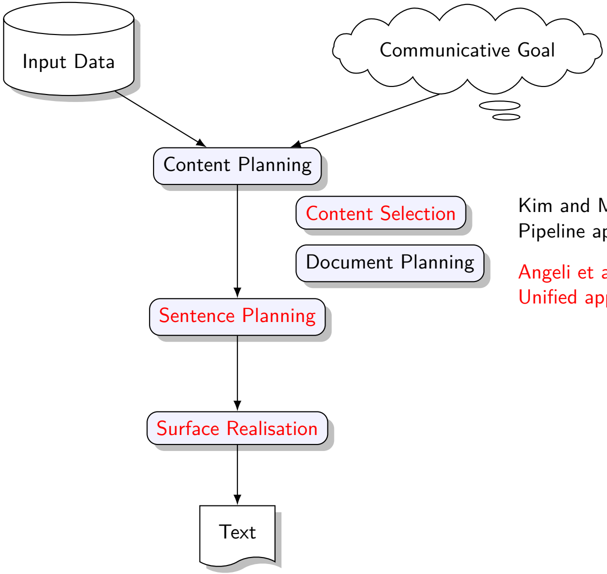


Kim and Mooney (2010)
Pipeline approach

Traditional NLG Pipeline



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Angeli et al. (2010)
Unified approach

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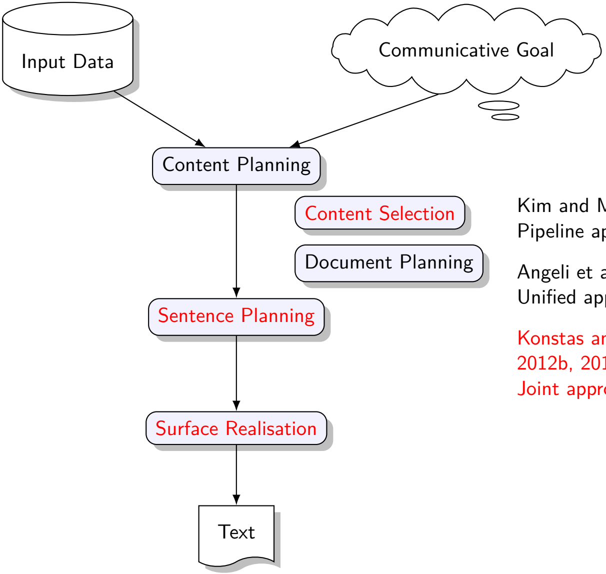

Kim and Mooney (2010)
Pipeline approach

Angeli et al. (2010)
Unified approach

Konstas and Lapata (2012a, 2012b, 2013b)
Joint approach

Input

- Input: database records **d**
- Output: words **w** corresponding to some records of **d**
- Each record $r \in \mathbf{d}$ has a type $r.t$ and fields f
- Fields have values $f.v$ and types $f.t$ (integer, categorical, string)

Cloud Sky Cover	
Time	**Percent (%)**
06:00-09:00	25-50
09:00-12:00	50-75

mostly cloudy,

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Konstas and Lapata, NAACL 2012

Unsupervised Concept-to-text Generation with Hypergraphs

Konstas and Lapata, JAIR 2013. In press

A Global Model for Concept-to-Text Generation, JAIR 2013, In press.

Key Idea

Temperature

Time	Min	Mean	Max
06:00-21:00	9	15	21

Cloud Sky Cover

Time	Percent (%)
06:00-09:00	25-50
09:00-12:00	50-75

Cloudy, with a low around 10. South wind between 15 and 30 mph.

Wind Speed

Time	Min	Mean	Max
06:00-21:00	15	20	30

Wind Direction

Time	Mode
06:00-21:00	S

Key Idea

Temperature

Time	Min	Mean	Max
06:00-21:00	9	15	21

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Wind Direction

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06:00-21:00	S

Key Idea

Temperature

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Cloud Sky Cover

Time	Percent (%)
06:00-09:00	25-50
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Wind Speed

Time	Min	Mean	Max
06:00-21:00	15	20	30

Wind Direction

Time	Mode
06:00-21:00	S

Cloudy, with a low around 10. South wind between 15 and 30 mph.

Partly cloudy, with a low around 9.
Breezy, with a south wind between 15 and 30 mph.

Grammar

Grammar

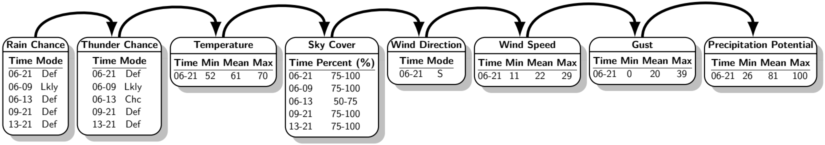
1. $\text{S} \rightarrow \text{R}(\textit{start})$

Grammar

1. $\mathrm{S} \rightarrow \mathrm{R}(start)$
2. $\mathrm{R}(r_i.t) \rightarrow \mathrm{FS}(r_j, start)\mathrm{R}(r_j.t) \mid \mathrm{FS}(r_j, start)$

$\mathrm{R}(skyCover_1.t) \rightarrow \mathrm{FS}(temperature_1, start)\mathrm{R}(temperature_1.t)$

Grammar



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2. $\mathrm{R}(r_i.t) \rightarrow \mathrm{FS}(r_j, start)\mathrm{R}(r_j.t) \mid \mathrm{FS}(r_j, start)$

$$\mathrm{R}(skyCover_1.t) \rightarrow \mathrm{FS}(temperature_1, start)\mathrm{R}(temperature_1.t)$$

Grammar

Rain Chance

Time	Mode
06-21	Def
06-09	Lkly
06-13	Def
09-21	Def
13-21	Def

Thunder Chance

Time	Mode
06-21	Def
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Time	Mode
06-21	S

Wind Speed

Time	Min	Mean	Max
06-21	11	22	29

Gust

Time	Min	Mean	Max
06-21	0	20	39

Precipitation Potential

Time	Min	Mean	Max
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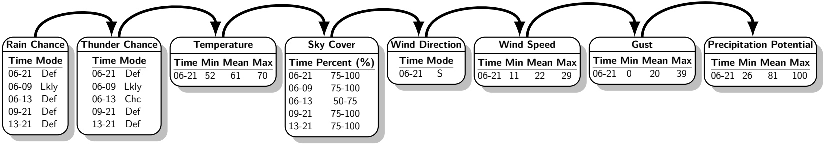
3. $\mathrm{FS}(r, r.f_i) \rightarrow \mathrm{F}(r, r.f_j)\mathrm{FS}(r, r.f_j) \mid \mathrm{F}(r, r.f_j)$

$$\mathrm{FS}(wSpeed_1, min) \rightarrow \mathrm{F}(wSpeed_1, max)\mathrm{FS}(wSpeed_1, max)$$

Grammar



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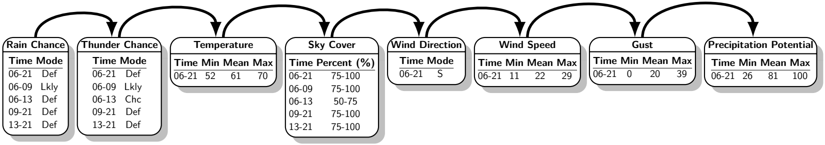
4. $\text{F}(r, r.f) \rightarrow \text{W}(r, r.f)\text{F}(r, r.f) \mid \text{W}(r, r.f)$

$$\text{F}(gust_1, min) \rightarrow \text{W}(gust_1, mean)\text{F}(gust_1, mean)$$

Grammar



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4. $\mathrm{F}(r, r.f) \rightarrow \mathrm{W}(r, r.f)\mathrm{F}(r, r.f) \mid \mathrm{W}(r, r.f)$
5. $\mathrm{W}(r, r.f) \rightarrow \alpha \mid \mathrm{g}(f.v)$

$\mathrm{W}(skyCover_1, \%) \rightarrow \text{cloudy } [\%.v = \text{‘75–100’}]$

Grammar

1. $S \rightarrow R(start)$
2. $R(r_i.t) \rightarrow FS(r_j, start) R(r_j.t) \mid FS(r_j, start)$
3. $FS(r, r.f_i) \rightarrow F(r, r.f_j) FS(r, r.f_j) \mid F(r, r.f_j)$
4. $F(r, r.f) \rightarrow W(r, r.f) F(r, r.f) \mid W(r, r.f)$
5. $W(r, r.f) \rightarrow \alpha \mid g(f.v)$

EM Training: dynamic program similar to the inside-outside algorithm

Decoding

$$\hat{g} = f\left(\arg\max_{g,h} p(g) \cdot p(\,g, h \,|\, \mathbf{d})\right)$$

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- Bottom-up Viterbi search
- Keep k-best derivations at each node, cube pruning (Chiang, 2007)
- $p(g)$ rescores derivations by linearly interpolating:
  - n-gram language model
  - dependency model (DMV; Klein and Manning, 2004)
- Implement using hypergraphs (Klein and Manning, 2001)

Decoding

Leaf nodes ϵ emit a k-best list of words

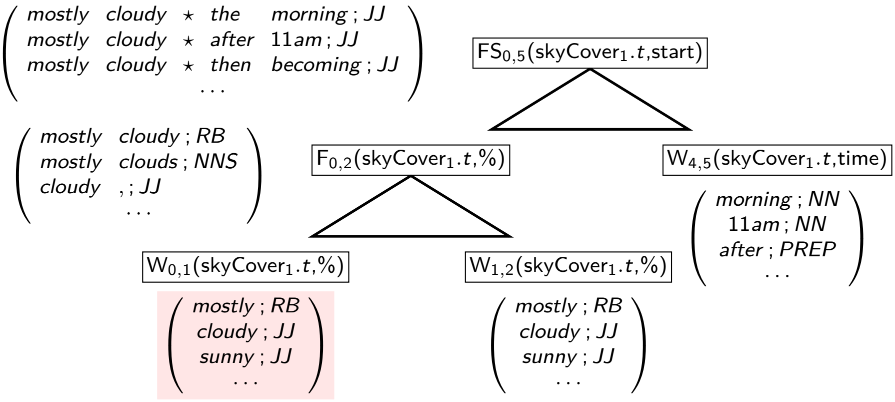
$$\boxed{W_{0,1}(\text{skyCover}_1.t, \%)}$$

$$\uparrow$$

$$\epsilon$$

$$\begin{pmatrix} \textit{mostly} ; \textit{RB} \\ \textit{cloudy} ; \textit{JJ} \\ \textit{sunny} ; \textit{JJ} \\ \ldots \end{pmatrix}$$

Decoding


mostly cloudy ⋆ the morning ; JJ
mostly cloudy ⋆ after 11am ; JJ
mostly cloudy ⋆ then becoming ; JJ
...
mostly cloudy ; RB
mostly clouds ; NNS
cloudy , ; JJ
...
$FS_{0,5}$(skyCover$_1$.t,start)
$F_{0,2}$(skyCover$_1$.t,%)
$W_{4,5}$(skyCover$_1$.t,time)
morning ; NN
11am ; NN
after ; PREP
...
$W_{0,1}$(skyCover$_1$.t,%)
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mostly ; RB
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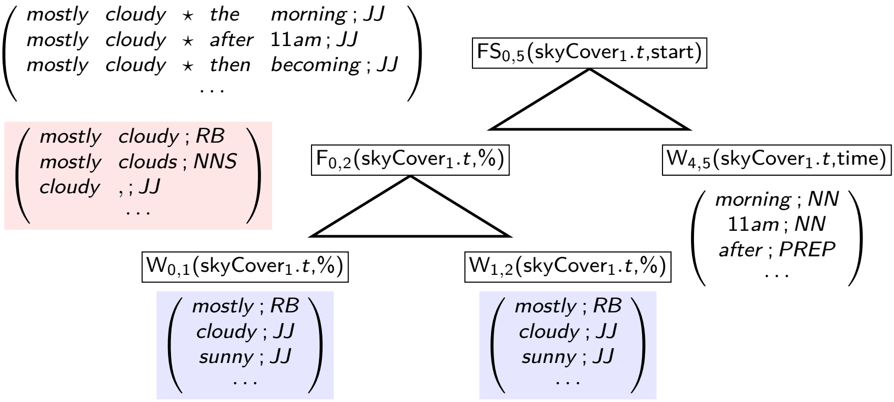
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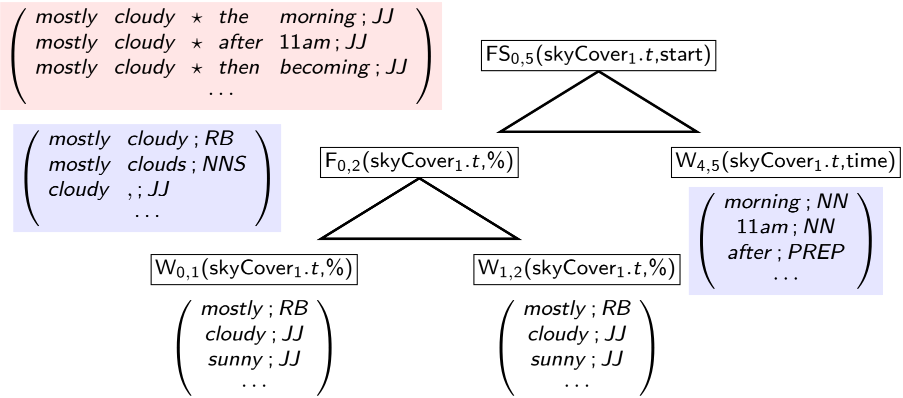
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mostly ; RB
cloudy ; JJ
sunny ; JJ
...
W1,2(skyCover1.t,%)
mostly ; RB
cloudy ; JJ
sunny ; JJ
...

Experimental Setup

Data

- RoboCup : simulated sportscasting [214 words] (Chen and Mooney, 2008)
- WeatherGov : weather reports [4 sents, 345 words] (Liang et al., 2009)
- Atis : flight booking [1 sent, 927 words] (Zettlemoyer and Collins, 2007)
- WinHelp : troubleshooting guides [4.3 sents, 629 words] (Branavan et al., 2009)

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Evaluation

- Automatic evaluation: BLEU-4
- Human evaluation: Fluency, Semantic Correctness

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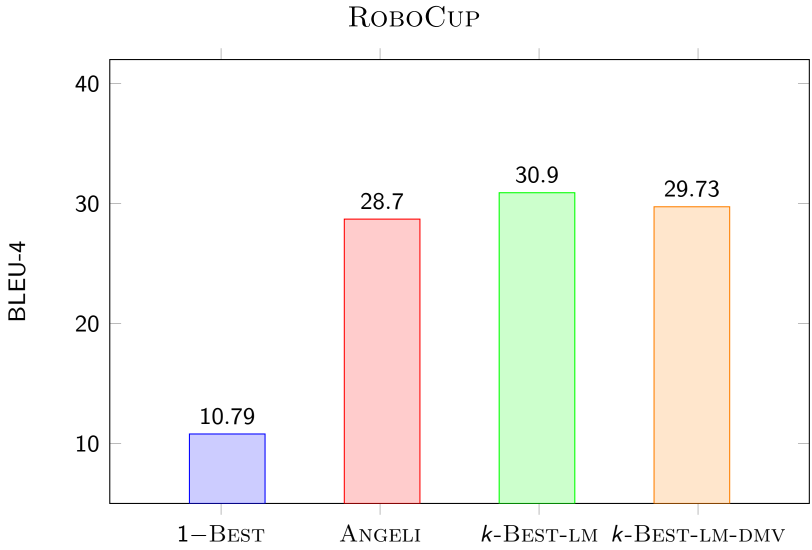
System Comparison

- 1−best, *k*-Best-lm, *k*-Best-lm-dmv
- Angeli et al. (2010)

Results: Automatic Evaluation



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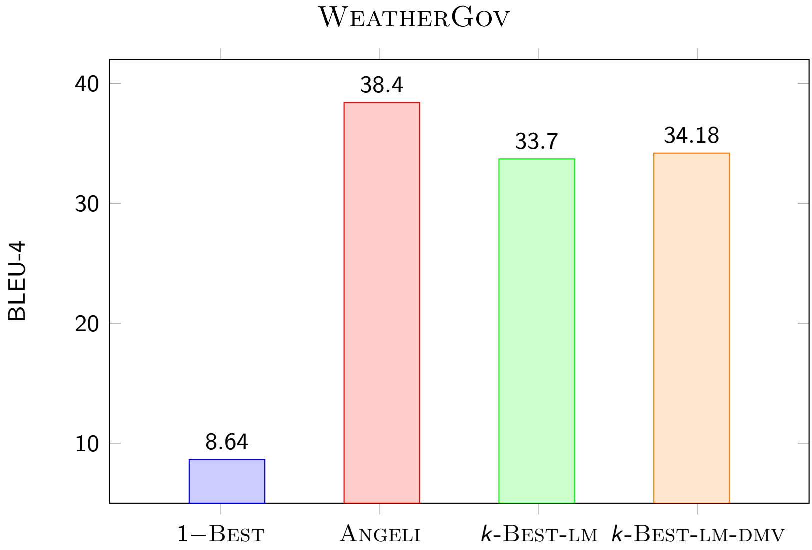

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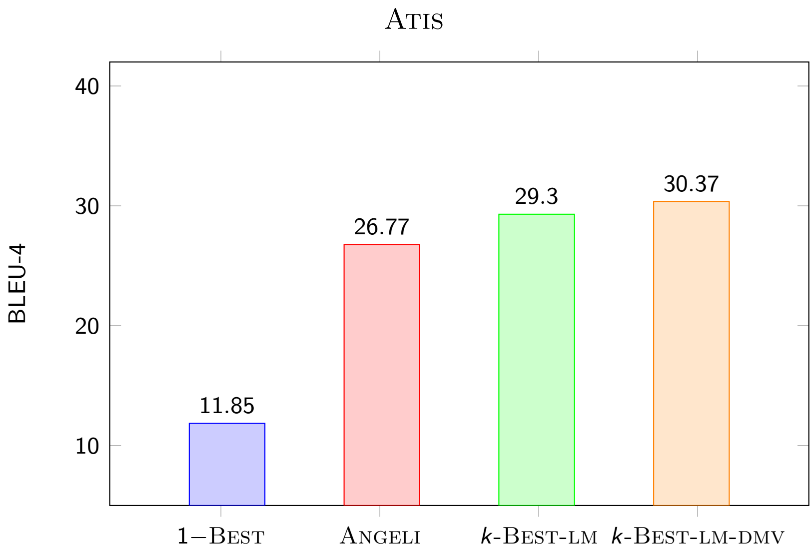

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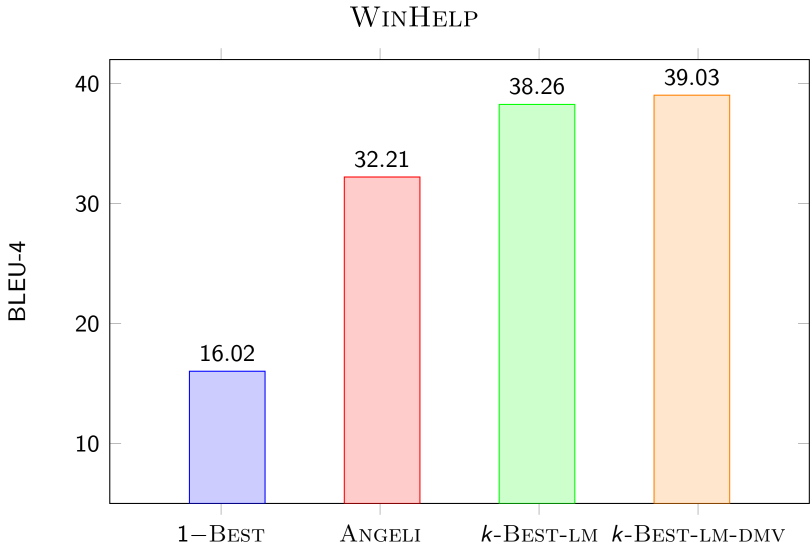


Output

WeatherGov

Temperature

Time	Min	Mean	Max
06:00-21:00	30	38	44

Cloud Sky Cover

Time	Percent (%)
06:00-21:00	75-100

Chance of Rain

Time	Mode
06:00-11:00	Slight Chance

Wind Speed

Time	Min	Mean	Max
06:00-21:00	6	6	7

Wind Direction

Time	Mode
06:00-21:00	ENE

Precipitation Potential (%)

Time	Min	Mean	Max
06:00-21:00	9	20	35

k-Best: **A chance of rain showers before 11am. Mostly cloudy, with a high near 44. East wind between 6 and 7 mph.**

Angeli: A chance of showers. Patchy fog before noon. Mostly cloudy, with a high near 44. East wind between 6 and 7 mph. Chance of precipitation is 35%

Human: A 40 percent chance of showers before 10am. Mostly cloudy, with a high near 44. East northeast wind around 7 mph.

Output

ATIS

Input:

Flight	
from	**to**
milwaukee	phoenix

Day	
day	**dep/ar/ret**
saturday	departure

Search	
type	**what**
query	flight

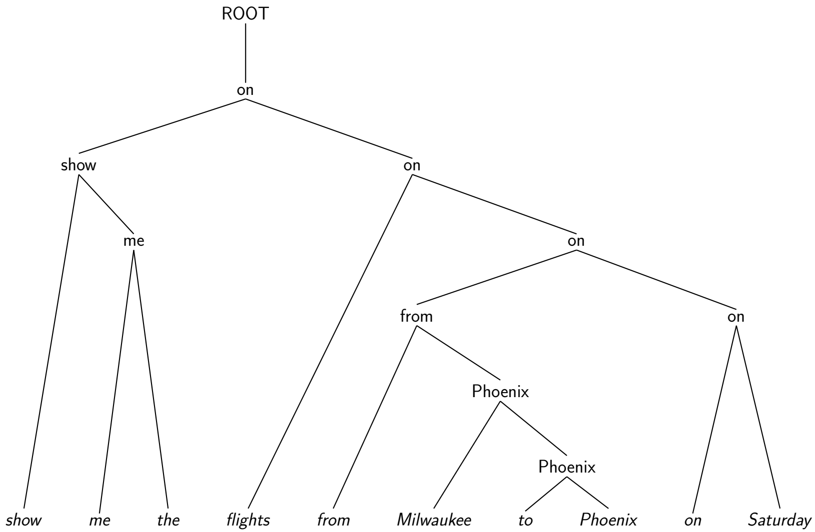
k-BEST: **What are the flights from Milwuakee to Phoenix on Saturday**

ANGELI : Show me the flights between Milwuakee and Phoenix on Saturday

HUMAN: Milwuakee to Phoenix on Saturday

Dependency Output

ATIS



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- Unsupervised end-to-end generation system
- Performance comparable to state-of-the-art

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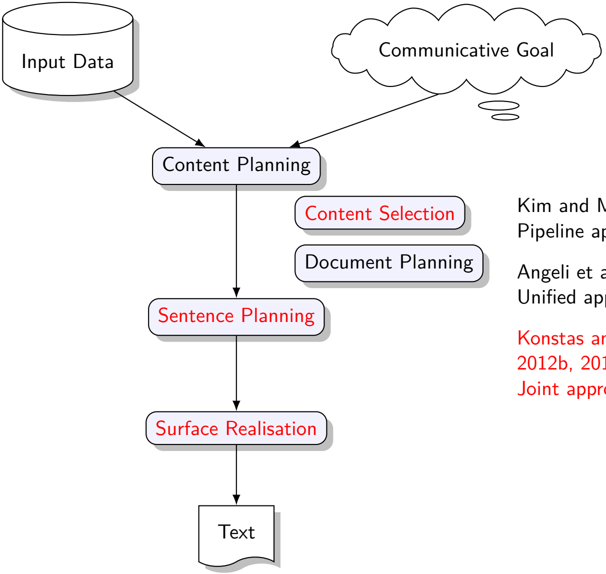
- What about document planning?

Konstas and Lapata, ACL 2013

Inducing Document Plans for Concept-to-text Generation, ACL 2013

Traditional NLG Pipeline

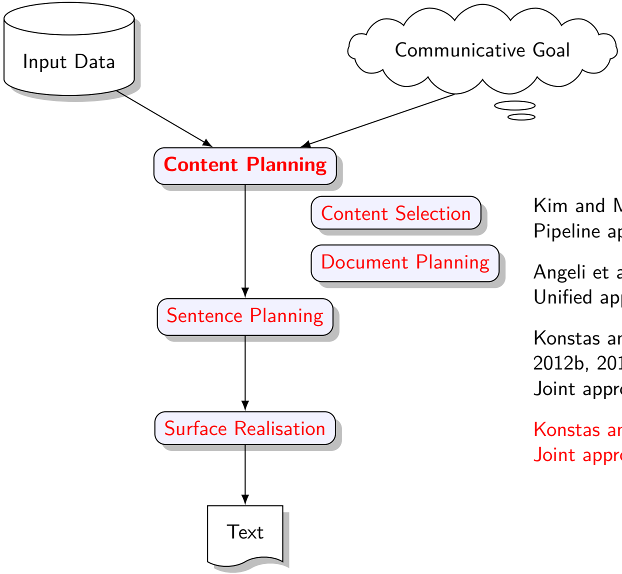


Kim and Mooney (2010)
Pipeline approach

Angeli et al. (2010)
Unified approach

Konstas and Lapata (2012a, 2012b, 2013a)
Joint approach

Traditional NLG Pipeline



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Unified approach

Konstas and Lapata (2012a, 2012b, 2013a)
Joint approach

Konstas and Lapata (2013a)
Joint approach

Key Idea

Desktop

Cmd	Name	Type
left-click	start	button

Start

Cmd	Name	Type
left-click	settings	button

Location

Name	Type
start menu	button
control panel	window

Start Target

Cmd	Name	Type
left-click	control panel	button

Navigate Window

Cmd	Name	Type
left-click	accounts and users	window

Context Menu

Cmd	Name	Type
left-click	advanced	tab

Action Context Menu

Cmd	Name	Type
left-click	advanced	button

Window Target

Cmd	Name	Type
double-click	users and passwords	item

Click start, point to settings, and then click control panel.

Double-click users and passwords.

On the advanced tab, click advanced.

Key Idea

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Start

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~~**Location**~~

Name	Type
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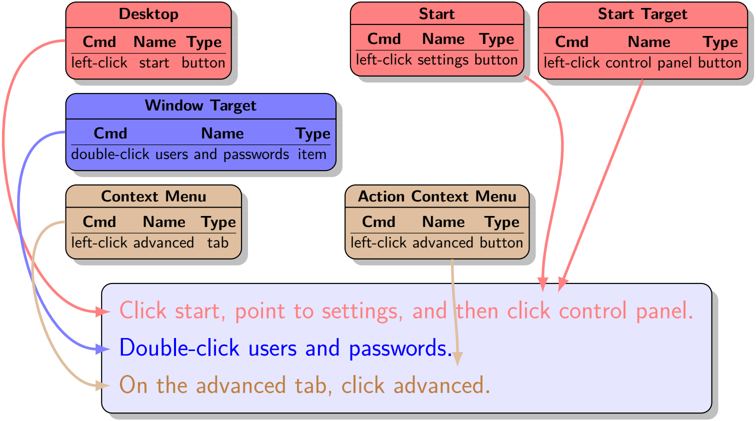
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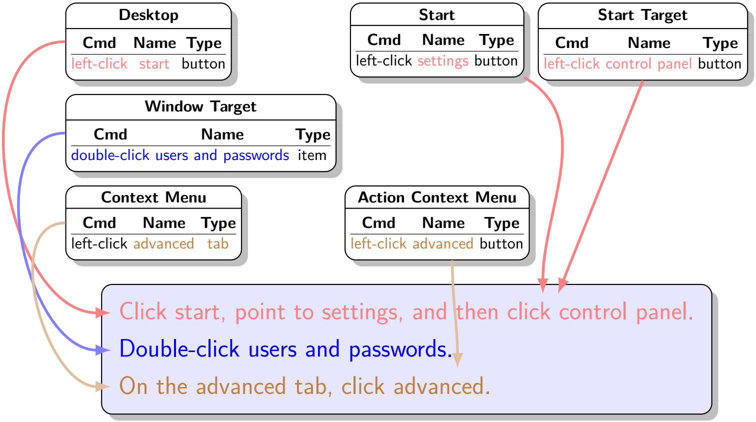
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- Re-use the generation model based on a PCFG grammar of input
- Replace existing locally coherent **Content Selection** model and incorporate global **Document Planning** (explore two solutions):

Patterns of record sequences *within* a sentence and *among* sentences

Rhetorical Structure Theory (Mann and Thompson, 1988) inspired plans

Planning with Record Sequences

Key idea: Grammar on sequences of record types (G_{RSE})

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1. Click start, point to settings, and then click control panel. $\|$ Double-click users and passwords. $\|$ On the advanced tab, click advanced. $\|$

Split a document into sentences, each terminated by a full-stop.

Planning with Record Sequences

Key idea: Grammar on sequences of record types (G_{RSE})

1. Click start, point to settings, and then click control panel. ‖ Double-click users and passwords. ‖ On the advanced tab, click advanced. ‖

   Split a document into sentences, each terminated by a full-stop.

2. $\frac{\text{desktop} \mid \text{start} \mid \text{start-target}}{\text{Click start, point to settings, and then click control panel.}}$ ‖ $\frac{\text{window-target}}{\text{Double-click users and passwords.}}$ ‖ $\frac{\text{contextMenu} \mid \text{action-contextMenu}}{\text{On the advanced tab, click advanced.}}$ ‖

   Then split a sentence further into a sequence of record types.

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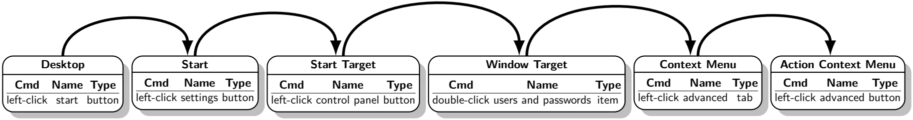
   Then split a sentence further into a sequence of record types.

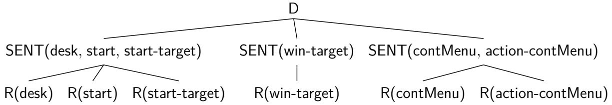
3. Goal: Learn patterns of record type sequences within and among sentences

Extended Grammar



1. ~~$\text{S} \rightarrow \text{R}(start)$~~
2. ~~$\text{R}(r_i.t) \rightarrow \text{FS}(r_j, start)\text{R}(r_j.t) \mid \text{FS}(r_j, start)$~~
3. $\text{FS}(r, r.f_i) \rightarrow \text{F}(r, r.f_j)\text{FS}(r, r.f_j) \mid \text{F}(r, r.f_j)$
4. $\text{F}(r, r.f) \rightarrow \text{W}(r, r.f)\text{F}(r, r.f) \mid \text{W}(r, r.f)$
5. $\text{W}(r, r.f) \rightarrow \alpha \mid \text{g}(f.v)$

Extended Grammar



1. $D \rightarrow SENT(t_i, \ldots, t_j) \ldots SENT(t_l, \ldots, t_m)$
2. $SENT(t_i, \ldots, t_j) \rightarrow R(r_a.t_i) \ldots R(r_k.t_j) \cdot$
3. $\mathrm{R}(r_i.t) \rightarrow \mathrm{FS}(r_j, start)$
4. $\mathrm{FS}(r, r.f_i) \rightarrow \mathrm{F}(r, r.f_j)\mathrm{FS}(r, r.f_j) \mid \mathrm{F}(r, r.f_j)$
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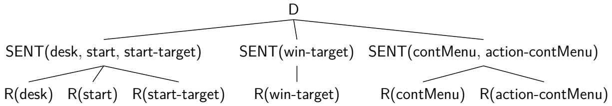

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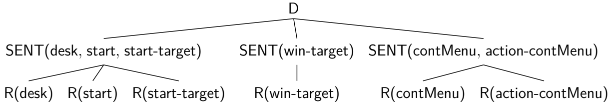
Straightforward solution: Embed the parameters with the original grammar and train using EM

Extended Grammar



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Plan B: Extract grammar rules from training data

Grammar Extraction

desktop	start	start-target	window-target
Click start,	point to settings,	and then click control panel.	Double-click users and passwords.

contextMenu	action-contextMenu
On the advanced tab ,	click advanced.

Liang et al. (2009)

Grammar Extraction

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Liang et al. (2009)

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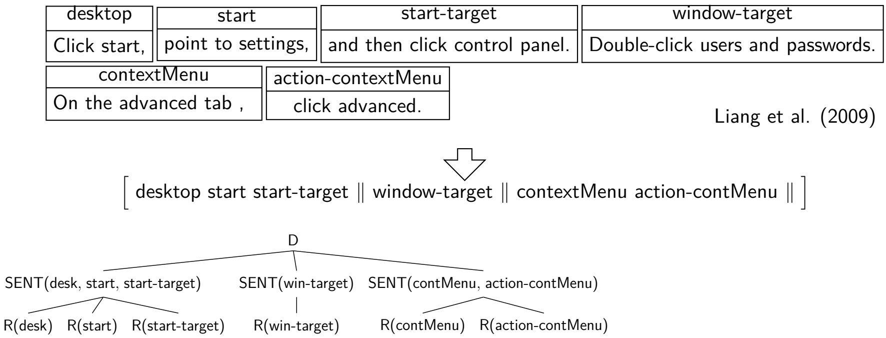
[desktop start start-target ‖ window-target ‖ contextMenu action-contMenu ‖]

Grammar Extraction



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Grammar Extraction

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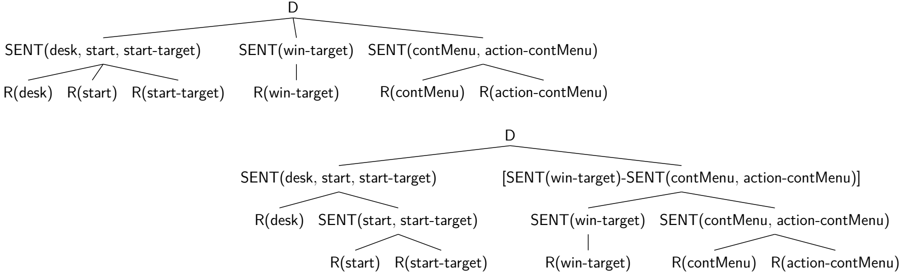
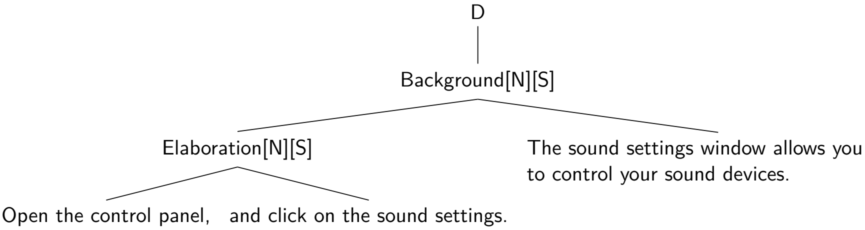
[desktop start start-target ‖ window-target ‖ contextMenu action-contMenu ‖]



Planning with Rhetorical Structure Theory

RST (Mann and Thompson, 1988)



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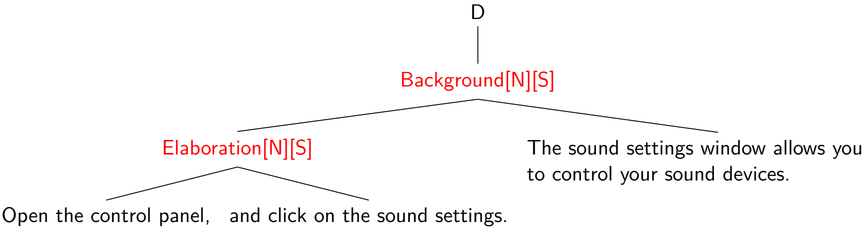

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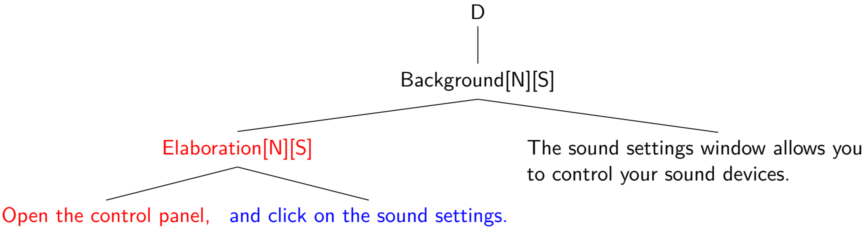

Planning with Rhetorical Structure Theory

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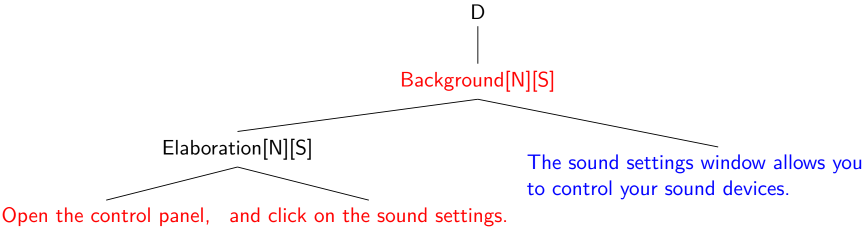

Planning with Rhetorical Structure Theory

Key idea: Grammar using RST relations (G_{RST})

Planning with Rhetorical Structure Theory

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Assumption

Each record in the database input corresponds to a unique non-overlapping span in the collocated text, and can be therefore mapped to an EDU.

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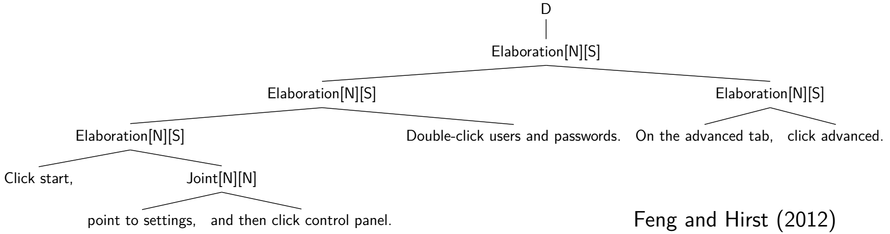
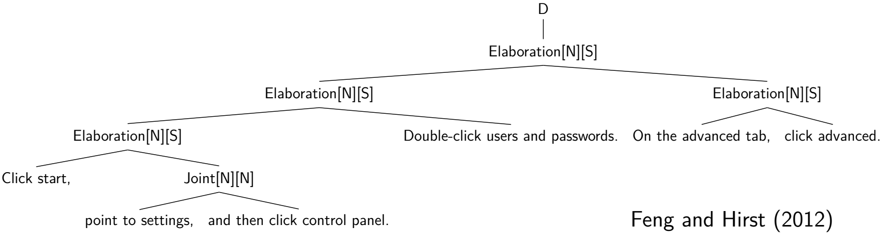
Grammar Extraction



Feng and Hirst (2012)

Grammar Extraction



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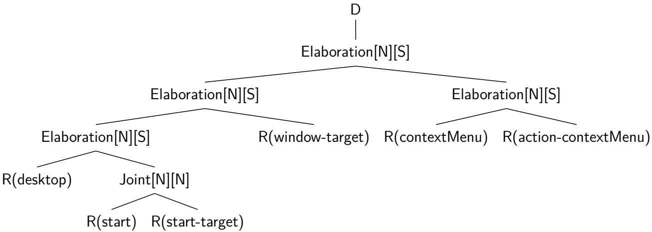

Extended Grammar

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Experimental Setup

Data

- WEATHERGOV : weather reports [4 sents, 345 words] (Liang et al., 2009)
- WINHELP : troubleshooting guides [4.3 sents, 629 words] (Branavan et al., 2009)

Experimental Setup

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Evaluation

- Automatic evaluation: BLEU-4
- Human evaluation: Fluency, Semantic Correctness, Coherence

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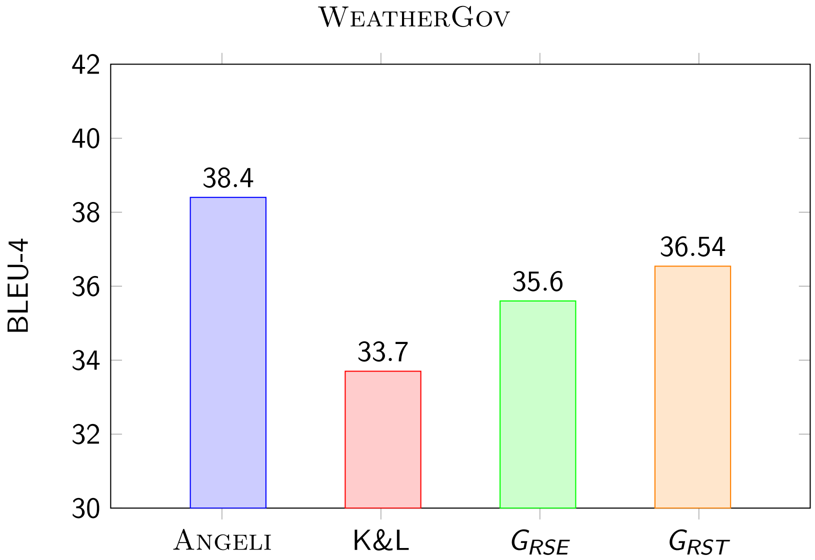
System Comparison

- G_{RSE}, G_{RST}
- Konstas and Lapata (2012a)
- Angeli et al. (2010)

Results: Automatic Evaluation



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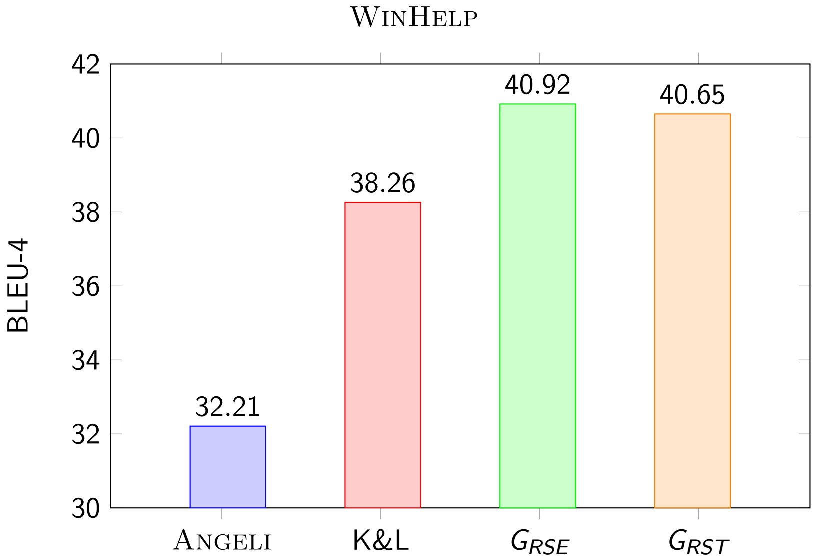
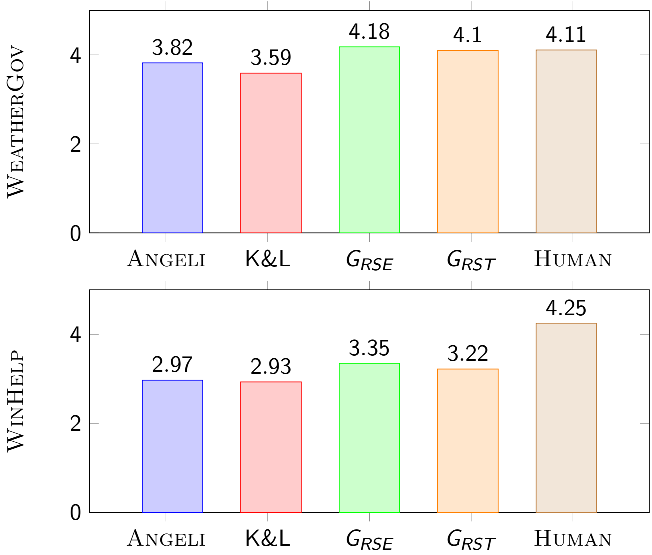


Results: Human Evaluation (Coherence)



Output

G_{RSE}	Click start, point to settings, and then click control panel. Double-click network and dial-up connections. Right-click local area connection, and then click properties. Click install, and then click add. Click network monitor driver, and then click ok.
K&L	Click start, point to settings, and then click control panel. Double-click network and dial-up connections. Double-click network and dial-up connections. Right-click local area connection, and then click ok.
HUMAN	Click start, point to settings, click control panel, and then double-click network and dial-up connections. Right-click local area connection, and then click properties. Click install, click protocol, and then click add. Click network monitor driver, and then click ok.

Conclusions

- End-to-end generation system that incorporates document planning
- Grammar-based approach allows for document planning naturally: all we need is a discourse grammar
- Provide two solutions for document plans:
  - Linguistically naive record sequence grammar (G_{RSE})
  - RST-inspired grammar (G_{RST})
- How about a more sophisticated content selection model on the field level?

Konstas and Lapata, ACL 2012

Concept-to-text Generation via Discriminative Reranking

Discriminative Reranking Model

Original Model

- Joint model allows for more global decisions
- **Forest rescoring** allows for rescoring k-best trees at all internal nodes via LM+DMV integration

Discriminative Reranking Model

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Discriminative Reranking Model

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Discriminative Reranking Model

- Use decoder of the original model as a baseline
- Introduce lexical and structural features up to the field level
- **Discriminative reranking** reranks k-best trees at all internal nodes
- Train using an online learning algorithm

Hypergraph Reranking

Flight

from	to
seattle	new york

Day Number

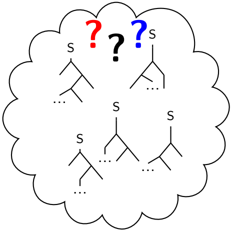
number	dep/ar
23	departure

Month

month	dep/ar
october	departure

Search

type	what
query	flight



Give me the flights leaving Seattle October 22nd coming back to New York

Hidden correspondence **h** between database **d** and words **w**

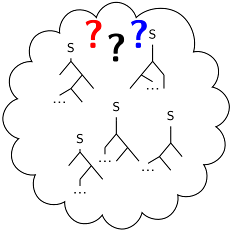
Hypergraph Reranking

Flight	
from	**to**
seattle	new york

Day Number	
number	**dep/ar**
23	departure

Month	
month	**dep/ar**
october	departure

Search	
type	**what**
query	flight



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$$(\widehat{\mathbf{g}}, \widehat{\mathbf{h}}) = \arg\max_{g,h} \alpha \cdot \Phi(\mathbf{d}, \widehat{\mathbf{g}}, \mathbf{h})$$

- $\Phi = (\Phi_1, \ldots, \Phi_m)$: high dimensional feature representation
- α : weight vector
- Learn α with averaged structured perceptron (Collins, 2002)

Hypergraph Reranking

Flight

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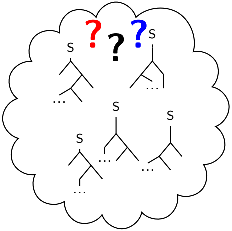

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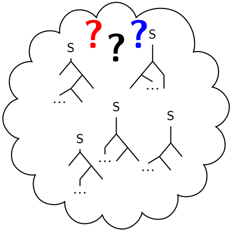

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Oracle Derivation

Oracle derivation $(\mathbf{w}^*, \mathbf{h}^+)$

- Use the decoder of the original model but observe the training text.
- $\mathbf{w}^*$: gold standard text
- $\mathbf{h}^+$: best latent configuration

Baseline Features

- Baseline Model Feature (local) : Log score of decoder of the original model

Baseline Features

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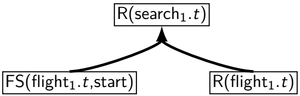
- Alignment Features (local) : Count of each PCFG rule



$\text{R}(r_i.t) \rightarrow \text{FS}(r_j, start)\text{R}(r_j.t)$

Lexical Features

- Word Bigrams/Trigrams (non-local)
- Number of Words per Field (local)
- Consecutive Word/Bigram/Trigram (non-local)

Lexical Features

- Word Bigrams/Trigrams (non-local)
- Number of Words per Field (local)
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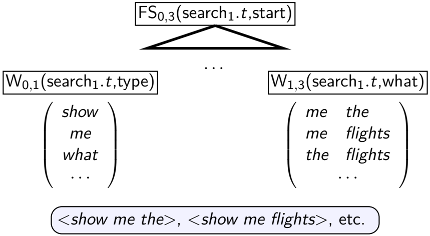

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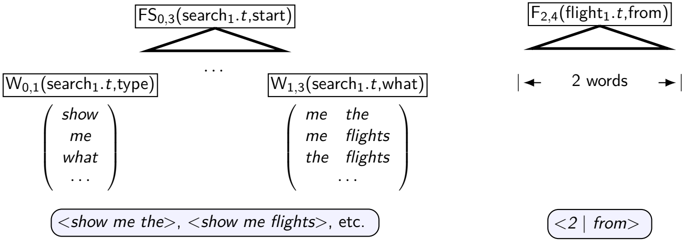

Content Selection at the Field Level Features

- Field Bigrams/Trigrams (non-local)
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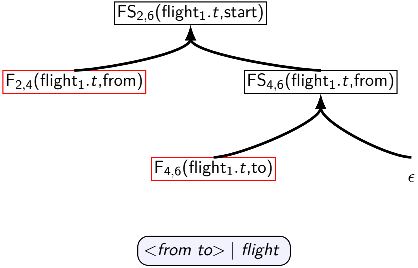
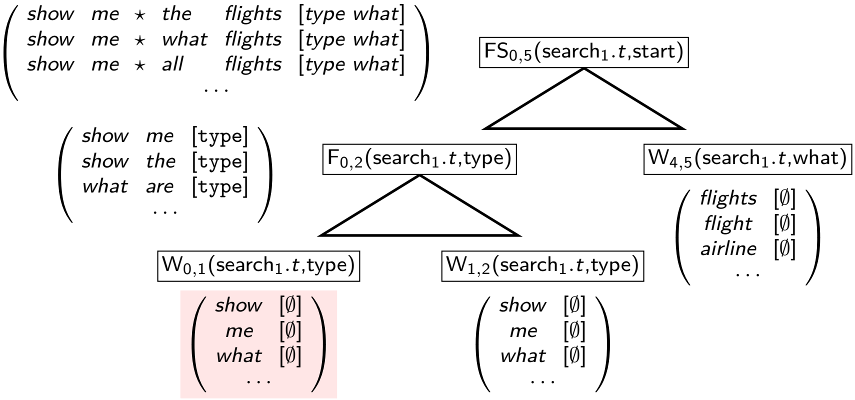


k-best Decoding

- Bottom-up Viterbi search
- Keep k-best derivations at each node, cube pruning (Chiang, 2007)
- Score of **j**-th derivation: $\alpha \cdot \Phi_L(e) + \alpha \cdot \Phi_N(< e, \mathbf{j} >)$

k-best Decoding



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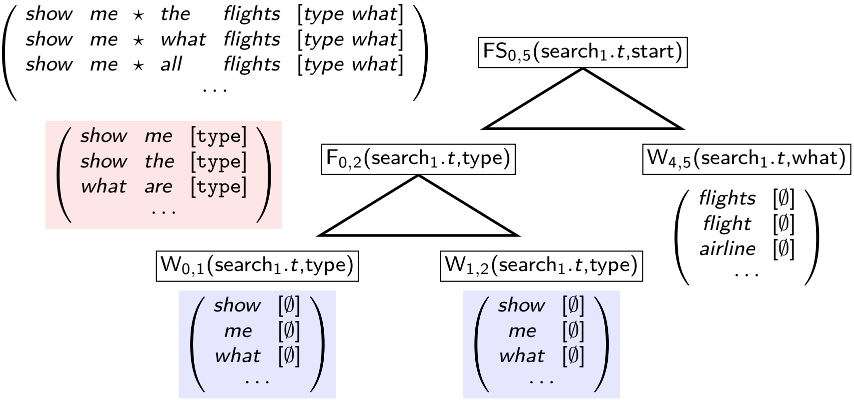

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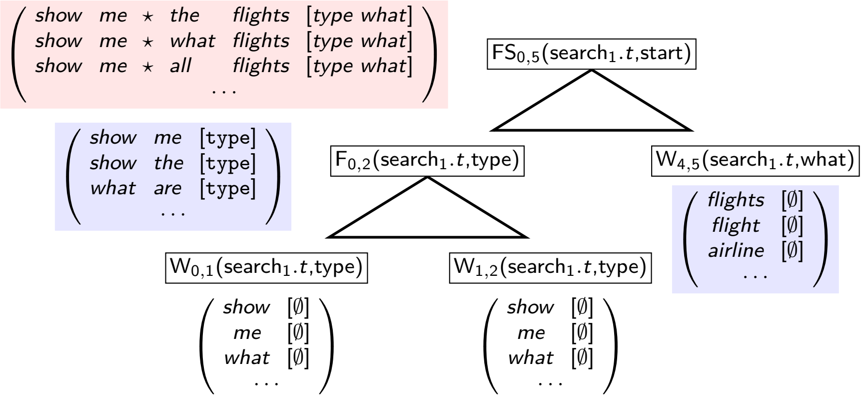

Experimental Setup

Data

- ATIS : flight booking [1 sent, 927 words] (Zettlemoyer and Collins, 2007)

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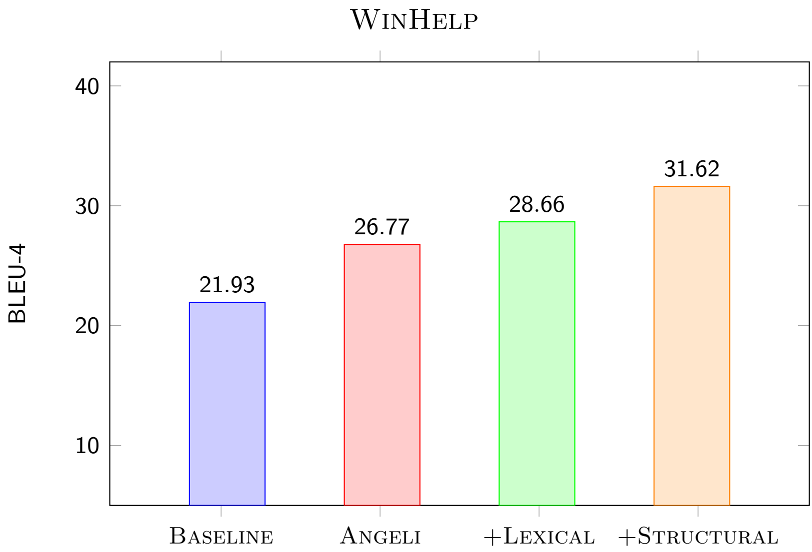
System Comparison

- Baseline: 1-BEST+BASE+ALIGN
- k-best (+Lexical): *k*-BEST+BASE+ALIGN+LEX
- k-best (+Structural): *k*-BEST+BASE+ALIGN+LEX+STR
- Angeli et al. (2010)

Results: Automatic Evaluation



Conclusions

- Discriminative reranking using the structured perceptron
- Introduced local and non-local features
- More sophisticated content selection on the field level

Where do we go from here?

- More challenging factual domains: biographies from Wikipedia
- More sophisticated sentence planning: aggregation, coreference resolution
- Real induction for document planning grammar G_{RSE}: ID/LP grammars
- Discriminative reranking: use of parallelisable online learning algorithms
- More engineering: scaling can be an issue for large documents
- Apply document planning grammars to summarisation

Thank you

Questions ?

Original Model Results: Human Evaluation (LM+DMV)

RoboCup

System	Fluency	SemCor
1-Best	2.47	2.33
k-Best	4.31	3.96
Angeli	4.03	3.70
Human	4.47	4.37

WeatherGov

System	Fluency	SemCor
1-Best	1.82	2.05
k-Best	3.92	3.30
Angeli	4.26	3.60
Human	4.61	4.03

Atis

System	Fluency	SemCor
1-Best	2.40	2.46
k-Best	4.01	3.87
Angeli	3.56	3.33
Human	4.10	4.01

WinHelp

System	Fluency	SemCor
1-Best	2.57	2.10
k-Best	3.41	3.05
Angeli	3.57	2.80
Human	4.15	4.04

Discriminative Reranking Results: Human Evaluation

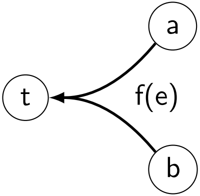
System	Fluency	SemCor
1-Best	2.70	3.05
k-Best	4.02	4.04
Angeli	3.74	3.17
Human	4.18	4.02

- *k*-Best significantly better than 1-best and Angeli ($\alpha < 0.01$)
- *k*-Best and Human are not significantly different

Hypergraphs

Definition

An ordered hypergraph H is a tuple $\langle N, E, t, \mathbf{R} \rangle$, where N is a finite set of nodes, E is a finite set of hyperarcs, $t \in N$ is a target node and $\mathbf{R}$ is the set of weights. Each hyperarc $e \in E$ is a triple $e = \langle T(e), h(e), f(e) \rangle$, where $h(e) \in N$ is its head node, $T(e) \in N^*$ is a set of tail nodes and $f(e)$ is a monotonic weight function $\mathbf{R}_{|T(e)|}$ to $\mathbf{R}$.



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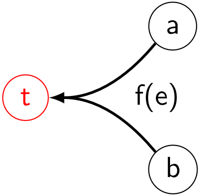

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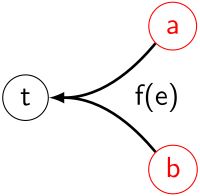

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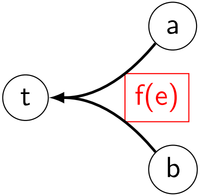
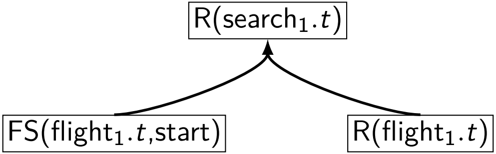


Hypergraph Construction

Map standard weighted CYK algorithm to hypergraph $H : \langle N, E, t, \mathbf{R} \rangle$



$$\begin{aligned} f(e) =& f(\text{FS}_{5,7}(\text{flight}_1.t, \textit{start})) \otimes f(\text{R}_{7,9}(\text{flight}_1.t)) \otimes \\ & w(\text{R}(\text{search}_1.t) \rightarrow \text{FS}(\text{flight}_1, \textit{start})\ \text{R}(\text{flight}_1.t)) \end{aligned}$$

$$\text{R}(r_i.t) \rightarrow \text{FS}(r_j, \textit{start}) \text{R}(r_j.t)$$

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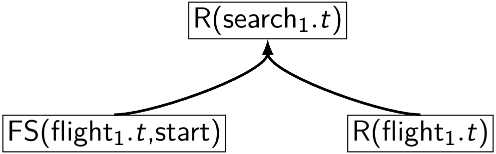

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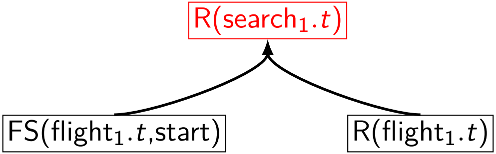

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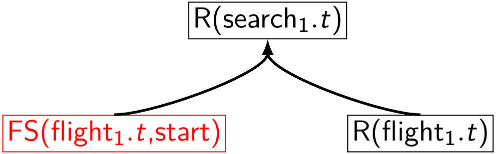

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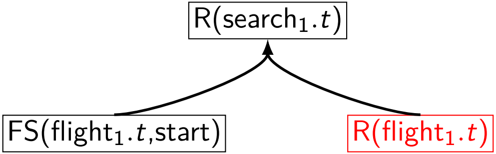

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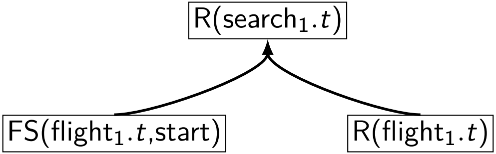

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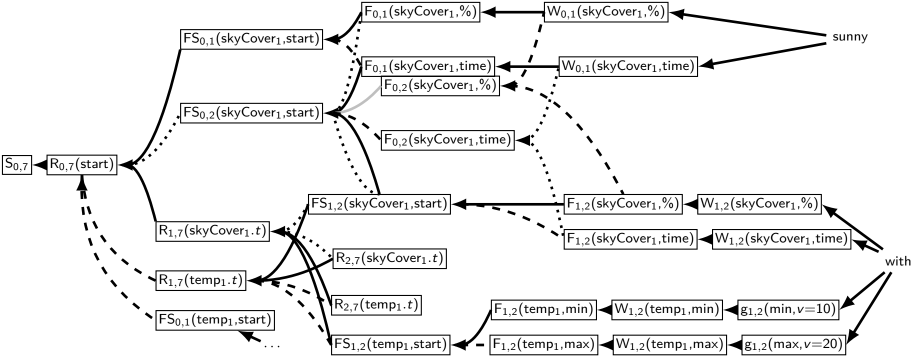
Hypergraph Example



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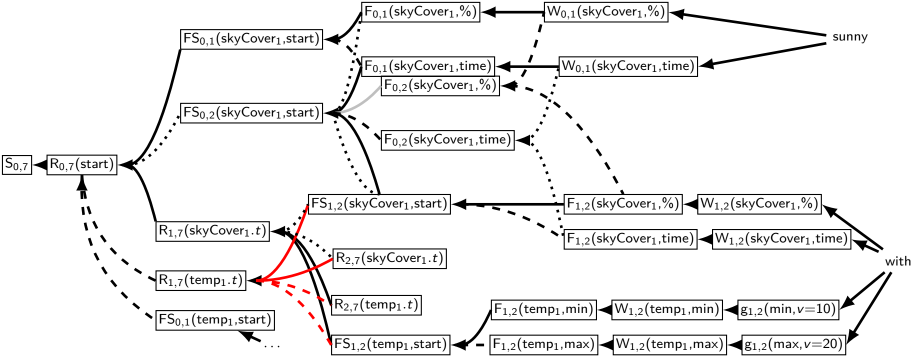

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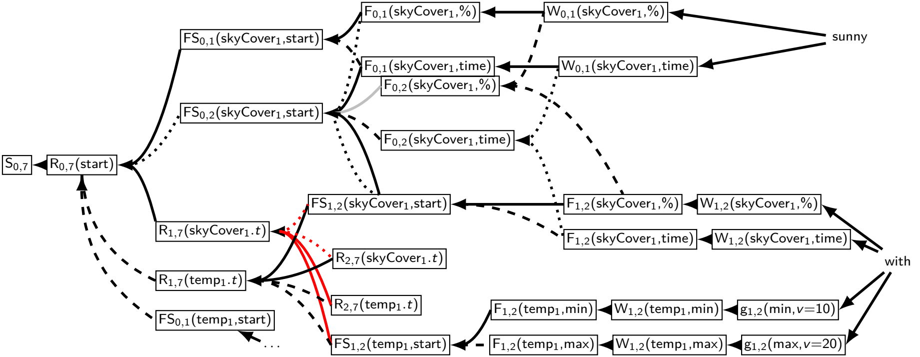

Determining Text Length

- Train a linear regression model
- Idea: The more records and fields that have values in the database $\rightarrow$ the more facts need to be uttered
- Input to the model: Flattened version of the database input, i.e. each feature is a record-field pair
- Feature values: Values vs Counts of Fields