

Learning to generate: Concept-to-text generation using machine learning

Ioannis Konstas

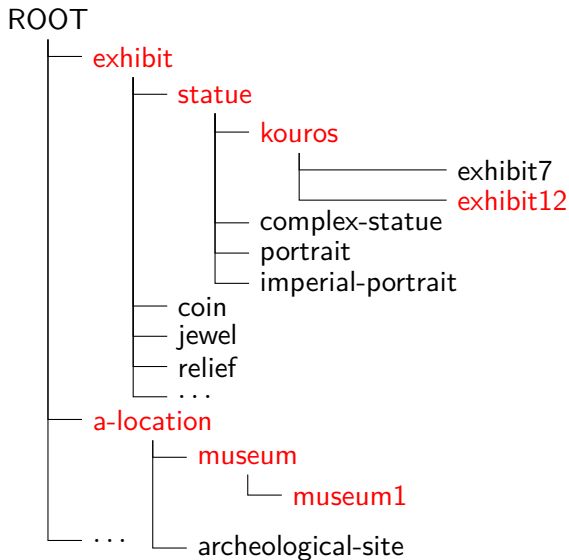
Institute for Language, Cognition and Computation
University of Edinburgh

Aberdeen, NLG Summer School
21 July 2015

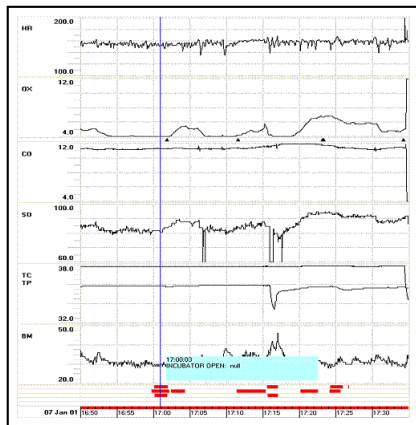
Introduction



Introduction



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Sensor Data

Full Descriptor	Time
SETTING;VENTIL;FiO2 (36%)	10.30
MEDICATION;Morphine	10.44
ACTION;CARE;TURN/ CHANGE POSITION;SUPINE	10.46-10.47
ACTION;RESP;HAND BABY	10.47-10.51
SETTING;VENTIL;FiO2 (60%)	10.47
ACTION;RESP;INTUBATE	10.51-10.52

Action Records

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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				Temperature				Wind Speed				Wind Direction		Gust				Precipitation Potential			
Time	Min	Mean	Max	Time	Min	Mean	Max	Time	Min	Mean	Max	Time	Mode	Time	Min	Mean	Max	Time	Min	Mean	Max
06-21	0	0	0	06-21	52	61	70	06-21	11	22	29	06-21	S	06-21	0	20	39	06-21	26	81	100

Sky Cover		Rain Chance		Snow Chance		Sleet Chance		Freezing Rain Chance		Thunder Chance	
Time	Percent (%)	Time	Mode	Time	Mode	Time	Mode	Time	Mode	Time	Mode
06-21	75-100	06-21	Def	06-21	-	06-21	-	06-21	-	06-21	Def
06-09	75-100	06-09	Lkly	06-09	-	06-09	-	06-09	-	06-09	Lkly
06-13	50-75	06-13	Def	06-13	-	06-13	-	06-13	-	06-13	Chc
09-21	75-100	09-21	Def	09-21	-	09-21	-	09-21	-	09-21	Def
13-21	75-100	13-21	Def	13-21	-	13-21	-	13-21	-	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.

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- Expert knowledge deployed for the creation of hand-crafted rules - single domain

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- Manually annotated corpora - discourse relations, alignments

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- Expert knowledge deployed for the creation of hand-crafted rules - single domain
- Manually annotated corpora - discourse relations, alignments
- Breakdown of process into a pipeline of modules

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What we will look into today?

- Recast NLG into a generative model
- Learn parameters from (un)-annotated data - multiple domains
- Search for the best parameters that fit the input and **decode** into text

Outline

- Problem Formulation
- Learning Alignments
- Pipeline Approach
- Joint Approaches

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- **Problem Formulation**
- **Learning Alignments**
- Pipeline Approach
- Joint Approaches

Input

- Input: database records \mathbf{d}
- Output: words \mathbf{w} corresponding to some records of \mathbf{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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Key Idea

Temperature

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

Cloud Sky Cover

Time	Percent (%)
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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

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Wind Speed

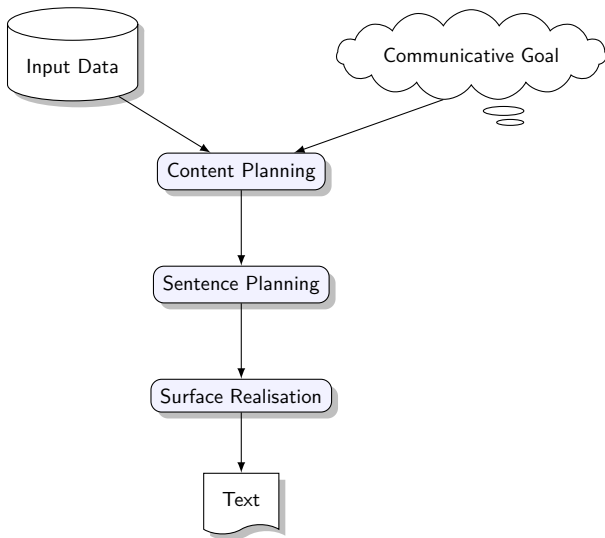
Time	Min	Mean	Max
06:00-21:00	15	20	30

Wind Direction

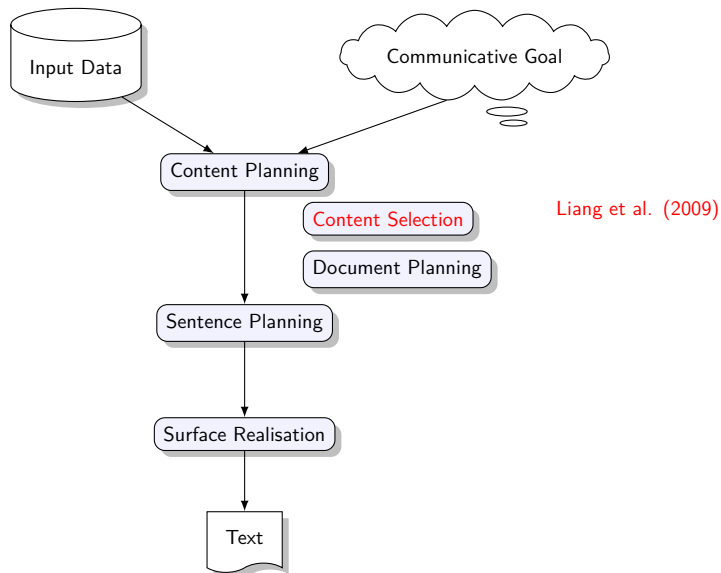
Time	Mode
06:00-21:00	S

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

Traditional NLG Pipeline



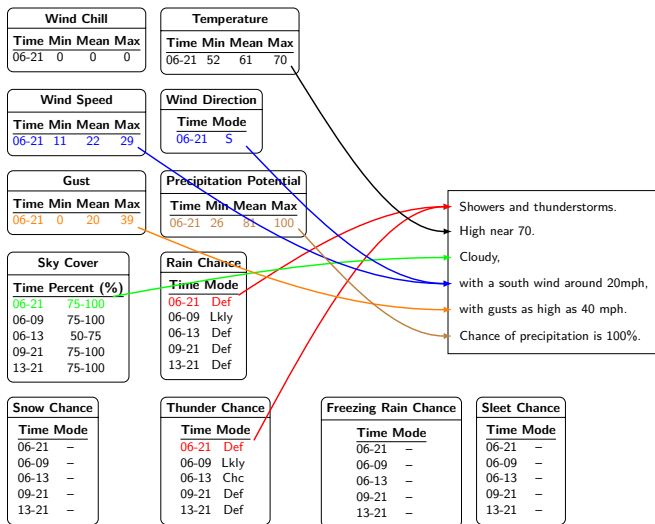
Traditional NLG Pipeline



Liang et al., ACL 2009

Learning Semantic Correspondences with Less Supervision

Alignment Task



Generative Story

- 1 Record choice: choose a sequence of records $\mathbf{r} = (r_1, \dots, r_{|\mathbf{r}|})$

$$p(\mathbf{r} | \mathbf{d}) = \prod_i^{|\mathbf{r}|} p(r_{i.t} | r_{i-1.t}) \frac{1}{|\mathbf{s}(r_{i.t})|}$$

$$p(\mathbf{r}, \mathbf{f}, \mathbf{c}, \mathbf{w} | \mathbf{d}) = p(\mathbf{r} | \mathbf{d}) p(\mathbf{f} | \mathbf{r}) p(\mathbf{c}, \mathbf{w} | \mathbf{r}, \mathbf{f}, \mathbf{d})$$

Generative Story

- ① Record choice: choose a sequence of records $\mathbf{r} = (r_1, \dots, r_{|\mathbf{r}|})$

$$p(\mathbf{r} | \mathbf{d}) = \prod_i^{|\mathbf{r}|} p(r_i.t | r_{i-1}.t) \frac{1}{|\mathbf{s}(r_i.t)|}$$

- ② Field choice: for each chosen record r_i , select a sequence of fields $\mathbf{f}_i = (f_{i1}, \dots, f_{i|f_i|})$

$$p(\mathbf{f} | r_i.t) = \prod_k^{|\mathbf{f}|} p(r_i.f_k | r_i.f_{k-1})$$

$$p(\mathbf{r}, \mathbf{f}, \mathbf{c}, \mathbf{w} | \mathbf{d}) = p(\mathbf{r} | \mathbf{d}) p(\mathbf{f} | \mathbf{r}) p(\mathbf{c}, \mathbf{w} | \mathbf{r}, \mathbf{f}, \mathbf{d})$$

Generative Story

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- 2 Field choice: for each chosen record r_i , select a sequence of fields $\mathbf{f}_i = (f_{i1}, \dots, f_{i|\mathbf{f}_i|})$

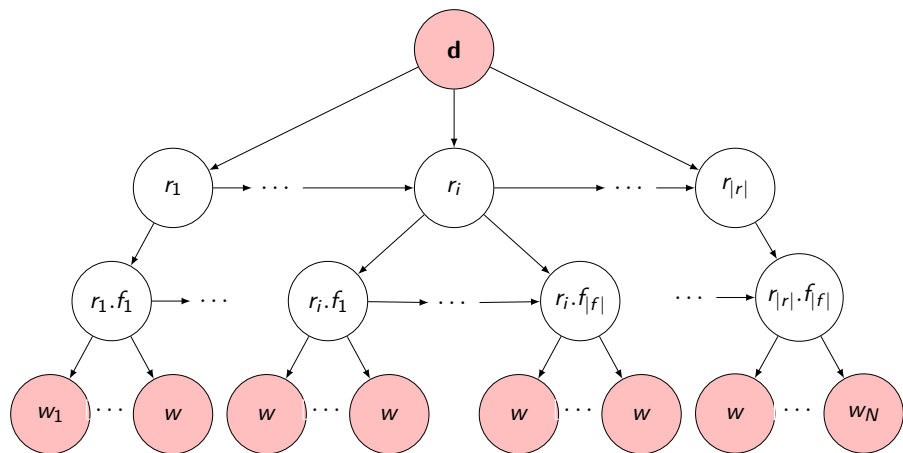
$$p(\mathbf{f} | r_i.t) = \prod_k^{|\mathbf{f}_i|} p(r_i.f_k | r_i.f_{k-1})$$

- 3 Word choice: for each chosen field f_{ik} , choose a number $c_{ik} > 0$ uniformly, and generate a sequence of c_{ik} words.

$$p(\mathbf{w} | r_i, r_i.f_k, r_i.f_k.t, c_{ik}) = \prod_j^{|\mathbf{w}|} p(w_j | r_i.t, r_i.f_k.v)$$

$$p(\mathbf{r}, \mathbf{f}, \mathbf{c}, \mathbf{w} | \mathbf{d}) = p(\mathbf{r} | \mathbf{d}) p(\mathbf{f} | \mathbf{r}) p(\mathbf{c}, \mathbf{w} | \mathbf{r}, \mathbf{f}, \mathbf{d})$$

Hierarchical Semi-Markov Model (HSMM)



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

Aligned Output

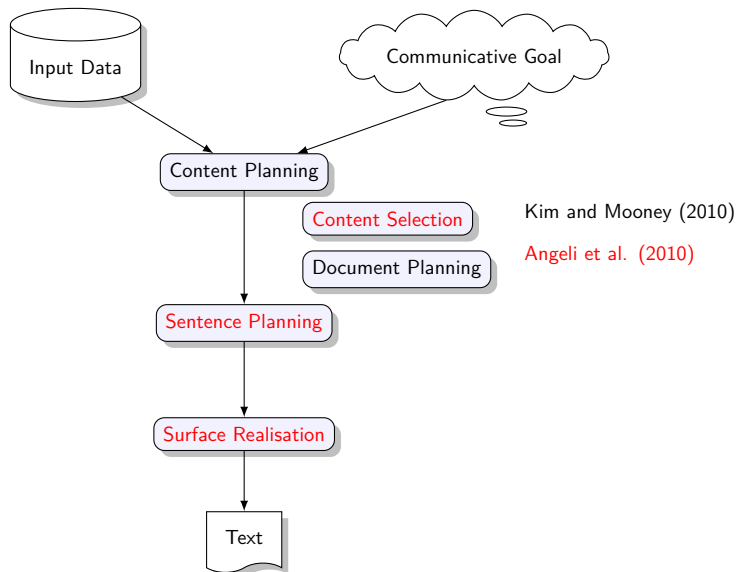
Records:	temperature ₁	skyCover ₁
Fields:	max= 70	percent= 75-100
Text:	<i>High near 70 .</i>	<i>Cloudy ,</i>

Records:	windDir ₁		windSpeed ₁		
Fields:		mode= S		mean= 20	
Text:	<i>with a</i>	<i>south</i>	<i>wind</i>	<i>around</i>	<i>20 mph .</i>

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- Problem Formulation
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- **Pipeline Approach**
- Joint Approaches

Traditional NLG Pipeline



Angeli et al., EMNLP 2010

A Simple Domain-Independent Probabilistic Approach to Generation

Generative Story

for $i = 1, 2, \dots$:

- 1 **choose** a record $r_i \in \mathbf{d}$

Generative Story

for $i = 1, 2, \dots$:

- 1 **choose** a record $r_i \in \mathbf{d}$
- 2 if $r_i = \text{STOP}$: **return**

Generative Story

for $i = 1, 2, \dots$:

- 1 **choose** a record $r_i \in \mathbf{d}$
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Generative Story

for $i = 1, 2, \dots$:

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- 4 **choose** a template $T_k \in r_i.t.f_j.T$

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Each **decision** is governed by a set of **feature templates**

Feature Templates

Record	R1	list of $k = 1, 2$ record types	$r_2.t = \text{temp} \wedge (r_1.t, r_0.t) = (\text{skyCover}, \text{START})$
	R2	set of prev record types	$r_2.t = \text{temp} \wedge \{r_1.t\} = \{\text{skyCover}\}$
	R3	record type already gen	$r_2.t = \text{temp} \wedge r_j.t \neq \text{temp}, \forall j < 2$
	R4	field values	$r_2.t = \text{temp} \wedge r_2.v[\text{min}] = 10, r_2.v[\text{max}] = 20$
	R5	STOP under LM	$r_3.t = \text{STOP} \times p_{LM}(\text{STOP} \text{degrees } .)$

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Template	W1	base/coarse	$B(T_2) = \langle \text{with a low around } [\text{min}] \rangle$ $C(T_2) = \langle \text{with a } [\text{time}] \text{ around } [\text{min}] \rangle$
	W2	field values	
	W3	1 _{st} word of T under LM	$p_{LM}(\text{with} \text{cloudy } ,)$

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$$p(\mathbf{c} | \mathbf{d}; \theta) = \prod_{j=1}^{|\mathbf{c}|} p(c_j | c_{<j}; \theta)$$

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$$p(\mathbf{c} | \mathbf{d}; \theta) = \prod_{j=1}^{|\mathbf{c}|} p(c_j | c_{<j}; \theta)$$

L-BFGS learning: Use Liang et al. (2009) alignments to compute features

Decoding

$$\hat{c}_j = \arg \max_{c_j} p(c_j | c_{<j}; \theta)$$

- Greedy search: choose the best decision \hat{c}_j until the STOP record is drawn

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- Greedy search: choose the best decision \hat{c}_j until the STOP record is drawn
- Alternatively, sample from the distribution $p(c_j | c_{<j}; \theta)$;
- Viterbi search over $\arg \max_{c_j} p(c_j | \mathbf{d}; \theta)$

Conclusions

- Generation recast into a generative story
- Ensemble of local decisions
- Discriminatively trained end-to-end generation system

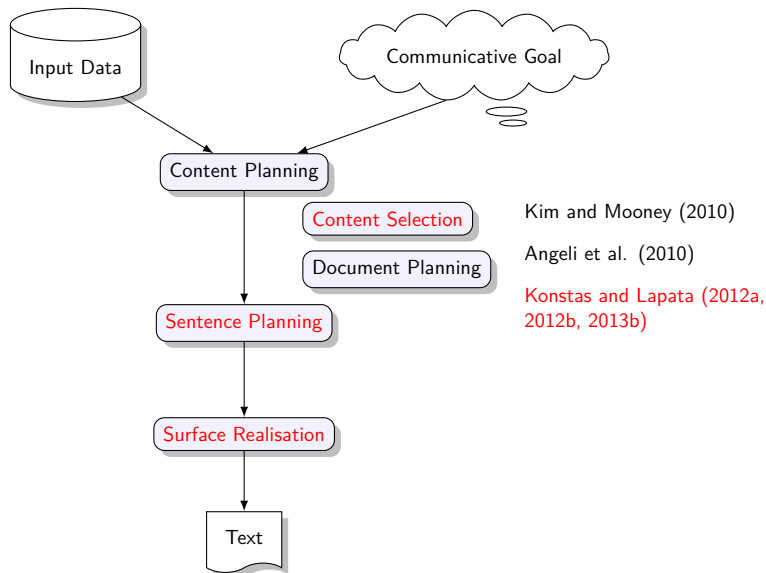
Conclusions

- Generation recast into a generative story
- Ensemble of local decisions
- Discriminatively trained end-to-end generation system
- How about we model generation **jointly** and learn **without** supervision?

Outline

- Problem Formulation
- Learning Alignments
- Pipeline Approach
- **Joint Approaches**

Traditional NLG Pipeline



Konstas and Lapata, NAACL 2012

Unsupervised Concept-to-text Generation with Hypergraphs

Konstas and Lapata, JAIR 2013

A Global Model for Concept-to-Text Generation

Grammar

Grammar

① $S \rightarrow R(\textit{start})$

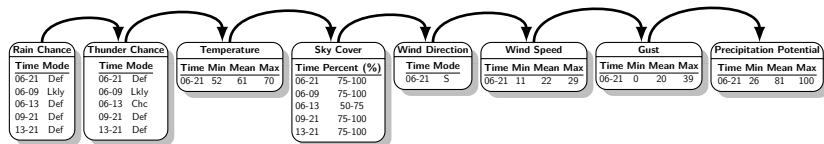
Grammar

$$① S \rightarrow R(\textit{start})$$

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

$$R(\textit{skyCover}_1.t) \rightarrow FS(\textit{temperature}_1, \textit{start})R(\textit{temperature}_1.t)$$

Grammar

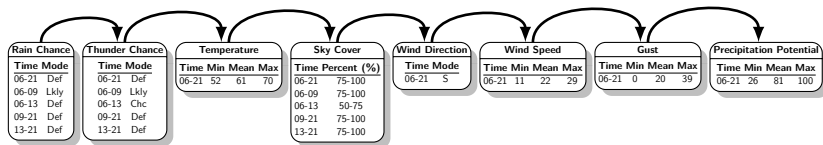


$$1 \quad S \rightarrow R(\text{start})$$

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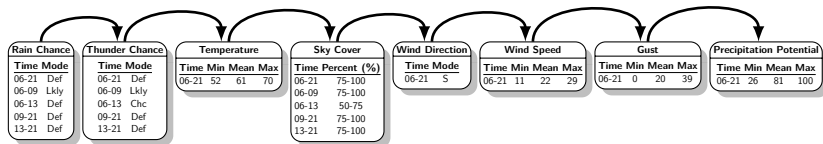
Grammar



- 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 $FS(r, r.fj) \rightarrow F(r, r.fj)FS(r, r.fj) \mid F(r, r.fj)$

$FS(wSpeed_1, min) \rightarrow F(wSpeed_1, max)FS(wSpeed_1, max)$

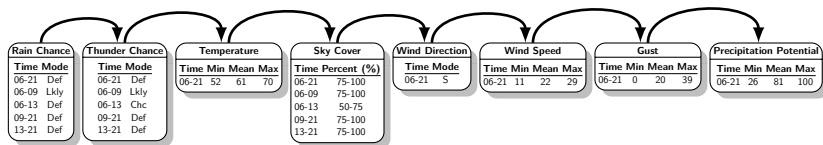
Grammar



- 1 $S \rightarrow R(start)$
- 2 $R(r_i.t) \rightarrow FS(r_j, start)R(r_j.t) \mid FS(r_j, start)$
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- 4 $F(r, r.f) \rightarrow W(r, r.f)F(r, r.f) \mid W(r, r.f)$

$F(gust_1, min) \rightarrow W(gust_1, mean)F(gust_1, mean)$

Grammar



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$W(\text{skyCover}_1, \%) \rightarrow \text{cloudy} [\%.v = \text{'75-100'}]$

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

Decoding

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

Decoding

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

- 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

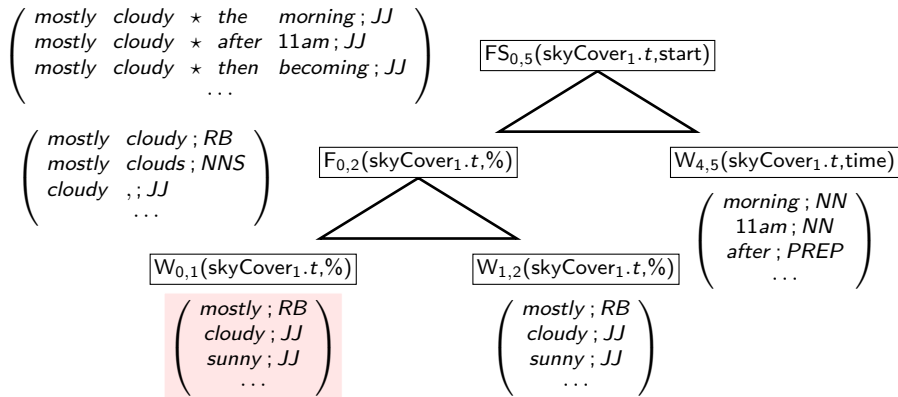
$W_{0,1}(\text{skyCover}_{1.t}, \%)$



ϵ

$\left(\begin{array}{l} \textit{mostly ; RB} \\ \textit{cloudy ; JJ} \\ \textit{sunny ; JJ} \\ \dots \end{array} \right)$

Decoding



Decoding

$\left(\begin{array}{l} \text{mostly cloudy} \star \text{the morning} ; JJ \\ \text{mostly cloudy} \star \text{after 11am} ; JJ \\ \text{mostly cloudy} \star \text{then becoming} ; JJ \\ \dots \end{array} \right)$

$FS_{0,5}(\text{skyCover}_1.t,\text{start})$

$\left(\begin{array}{l} \text{mostly cloudy} ; RB \\ \text{mostly clouds} ; NNS \\ \text{cloudy} ; JJ \\ \dots \end{array} \right)$

$F_{0,2}(\text{skyCover}_1.t,\%)$

$W_{4,5}(\text{skyCover}_1.t,\text{time})$

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

$W_{1,2}(\text{skyCover}_1.t,\%)$

$\left(\begin{array}{l} \text{morning} ; NN \\ 11\text{am} ; NN \\ \text{after} ; PREP \\ \dots \end{array} \right)$

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

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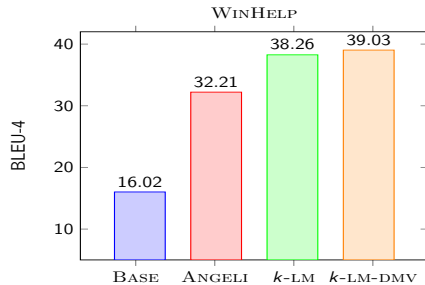
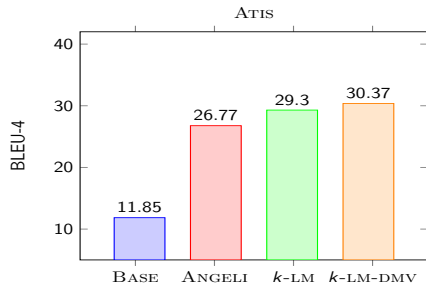
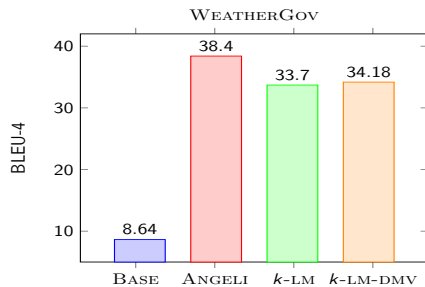
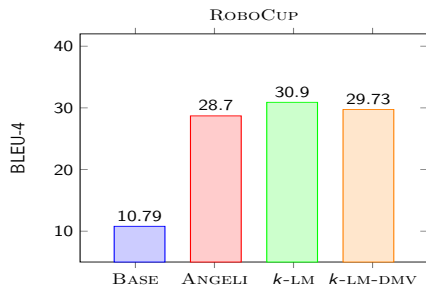
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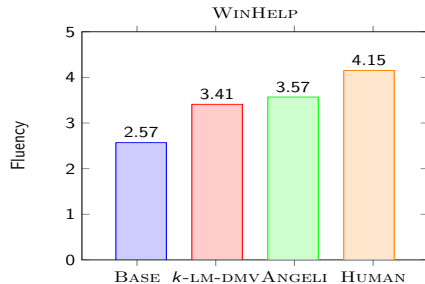
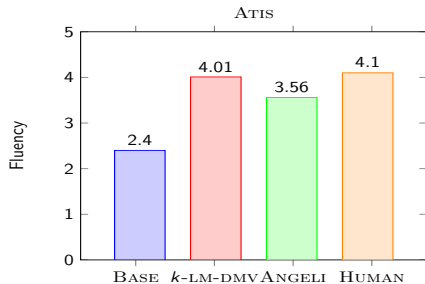
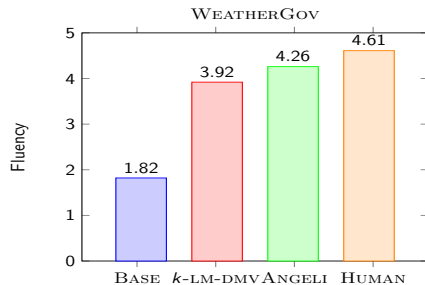
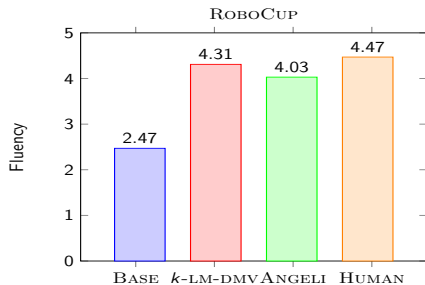
System Comparison

- 1-best, k -BEST-LM, k -BEST-LM-DMV
- Angeli et al. (2010)

Results: Automatic Evaluation



Results: Human Evaluation (Fluency)



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

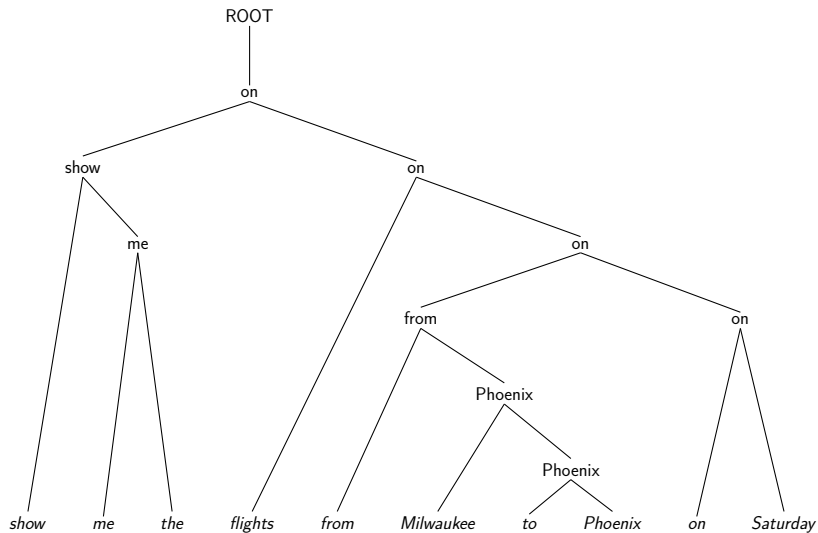
ATIS

	Flight	Day	Search												
Input:	<table border="1"> <tr> <td>from</td> <td>to</td> </tr> <tr> <td>milwaukee</td> <td>phoenix</td> </tr> </table>	from	to	milwaukee	phoenix	<table border="1"> <tr> <td>day</td> <td>dep/ar/ret</td> </tr> <tr> <td>saturday</td> <td>departure</td> </tr> </table>	day	dep/ar/ret	saturday	departure	<table border="1"> <tr> <td>type</td> <td>what</td> </tr> <tr> <td>query</td> <td>flight</td> </tr> </table>	type	what	query	flight
from	to														
milwaukee	phoenix														
day	dep/ar/ret														
saturday	departure														
type	what														
query	flight														

- k*-BEST: **What are the flights from Milwaukee to Phoenix on Saturday**
- ANGELI : Show me the flights between Milwaukee and Phoenix on Saturday
- HUMAN: Milwaukee to Phoenix on Saturday

Dependency Output

ATIS



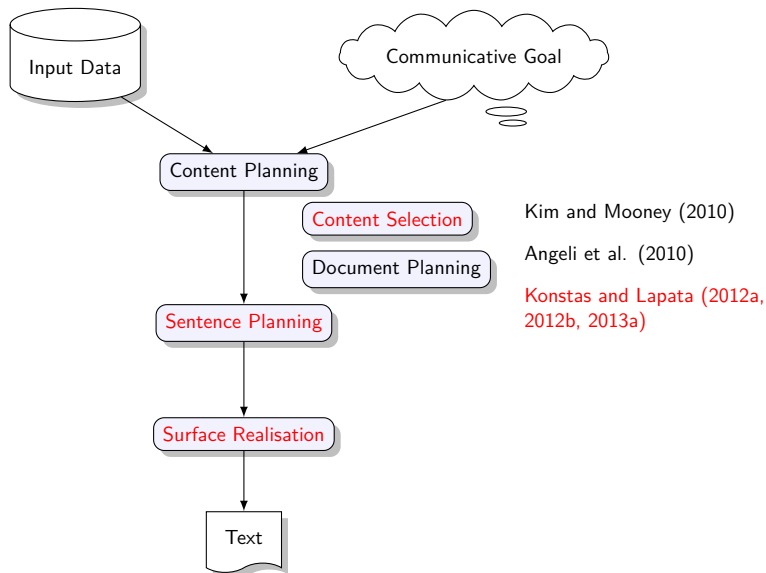
Conclusions

- Generation as parsing problem
- Unsupervised end-to-end generation system
- Performance comparable to state-of-the-art

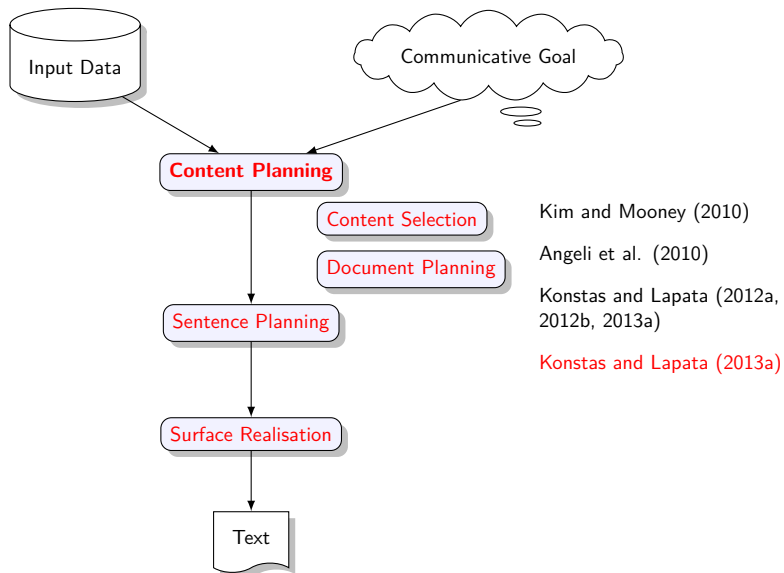
Conclusions

- Generation as parsing problem
- Unsupervised end-to-end generation system
- Performance comparable to state-of-the-art
- What about **document planning?**

Traditional NLG Pipeline



Traditional NLG Pipeline



Konstas and Lapata, EMNLP 2013

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

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.

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left-click	start	button

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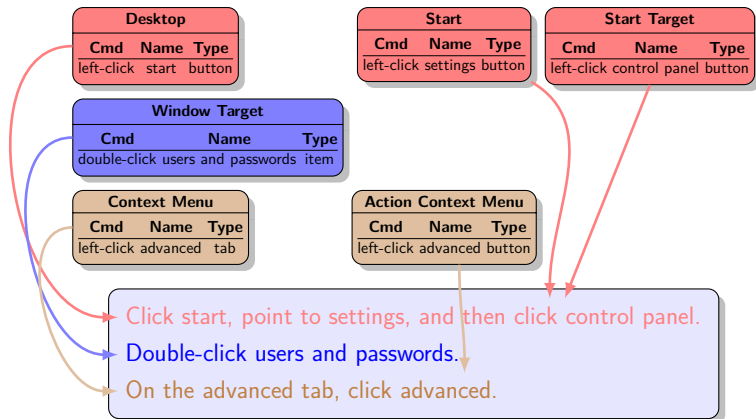
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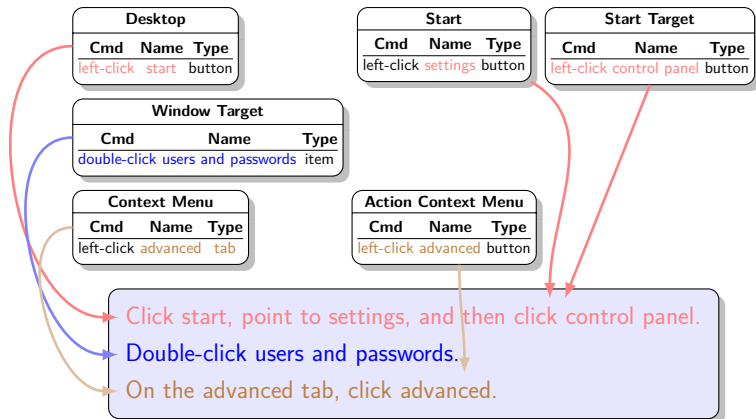
Action Context Menu		
Cmd	Name	Type
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Patterns of record sequences *within* a sentence and *among* sentences

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

Planning with Record Sequences

Key idea: Grammar on sequences of record types

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

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

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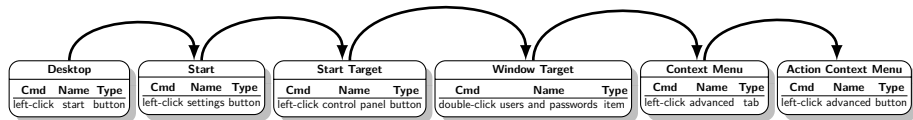
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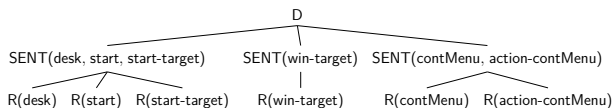
- 3 Goal: Learn patterns of record type sequences **within** and **among** sentences

Extended Grammar



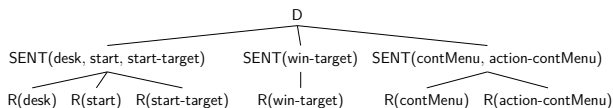
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Extended Grammar



- 1 $D \rightarrow SENT(t_i, \dots, t_j) \dots SENT(t_l, \dots, t_m)$
- 2 $SENT(t_i, \dots, t_j) \rightarrow R(r_a.t_i) \dots R(r_k.t_j) \cdot$
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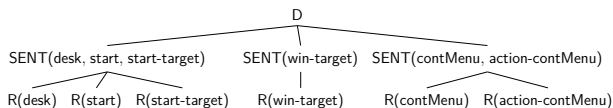
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Plan B: Extract grammar rules from training data

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)

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

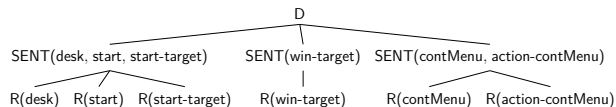
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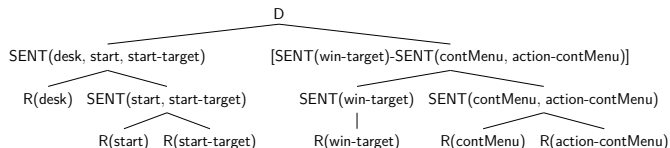
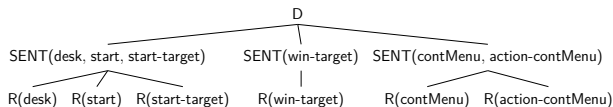
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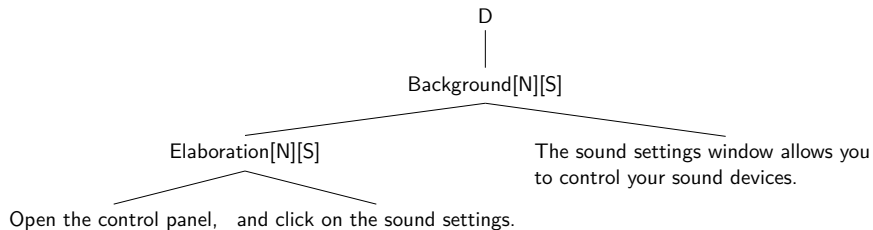


[desktop start start-target || window-target || contextMenu action-contMenu ||]



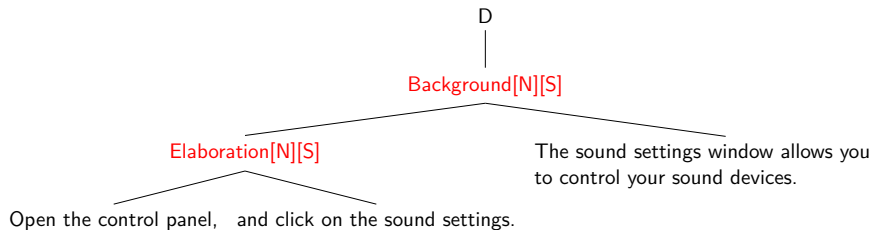
Planning with Rhetorical Structure Theory

RST (Mann and Thompson, 1988)



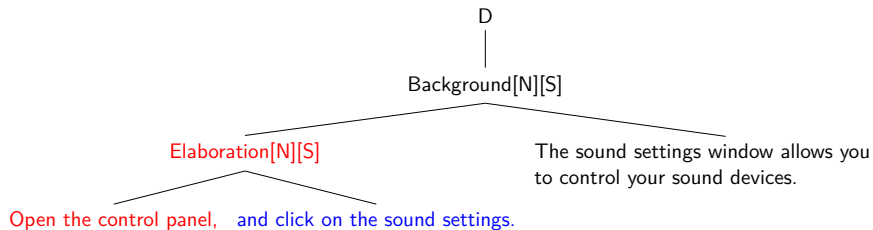
Planning with Rhetorical Structure Theory

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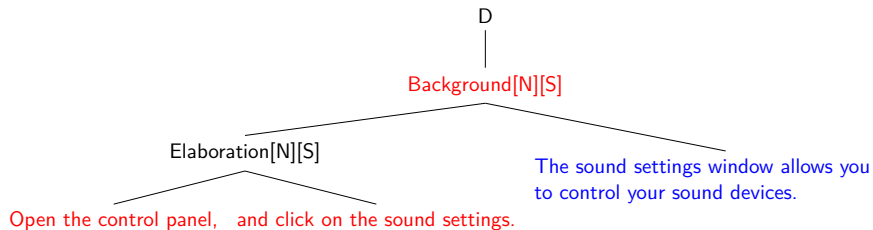
Planning with Rhetorical Structure Theory

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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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Click start,	point to settings,	and then click control panel.	Double-click users and passwords.
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Grammar Extraction

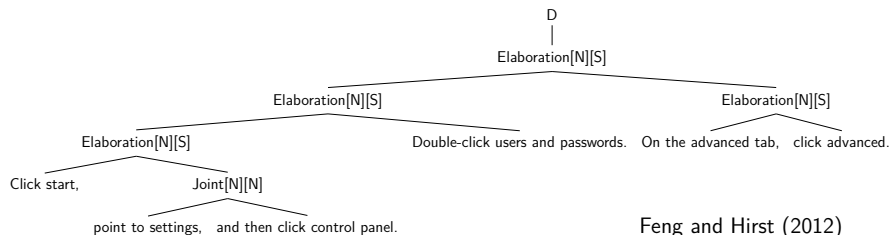
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contextMenu	action-contextMenu		
On the advanced tab ,	click advanced.		

Liang et al. (2009)

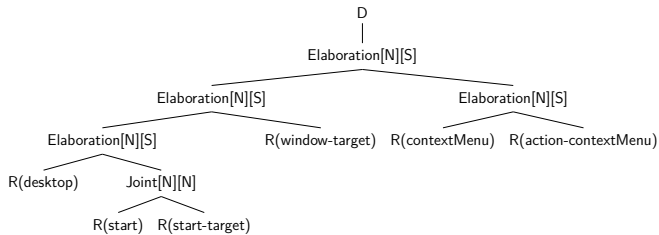
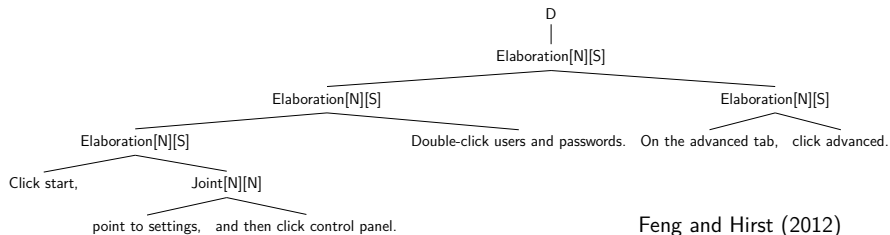


[Click start,]^{desktop} [point to settings,]^{start} [and then click control panel.]^{start-target}
 [Double-click users and passwords.]^{window-target} [On the advanced tab,]^{contextMenu}
 [click advanced.]^{action-contextMenu}

Grammar Extraction



Grammar Extraction



Extended Grammar

- 1 G_{RST}
- 2 $R(r_i.t) \rightarrow FS(r_j, start)$
- 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 $W(r, r.f) \rightarrow \alpha \mid g(f.v) \mid gen_str(f.v, i)$

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)

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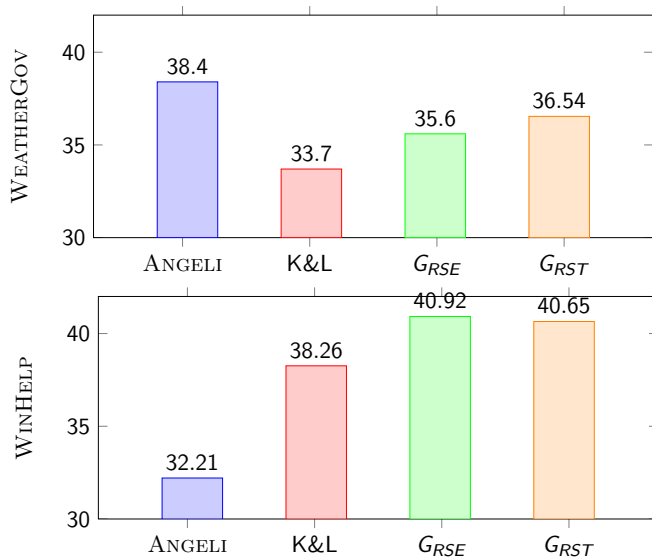
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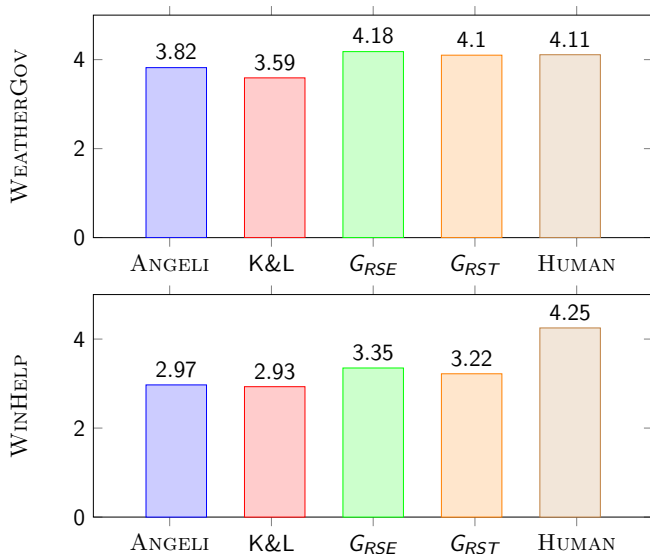
System Comparison

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

Results: Automatic Evaluation (BLEU-4)



Results: Human Evaluation (Coherence)



Output

GRSE

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})

Recap

- Recast NLG into a generative model
 - History-based local decisions - Add more features
 - Hierarchical joint model - Add more layers
- Learn parameters from (un)-annotated data - multiple domains
- **Decoding**: greedy search, k -best Viterbi search

Where do we go from here?

- Generate from more open-ended formalisms: AMR
- More challenging factual domains: biographies from Wikipedia
- More sophisticated sentence planning: aggregation, referring expressions
- More engineering: address sparsity, with Deep Learning
- Apply document planning grammars to summarisation

Thank you

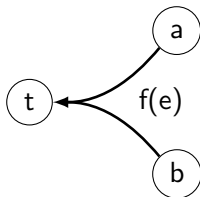
Questions ?



Hypergraphs

Definition

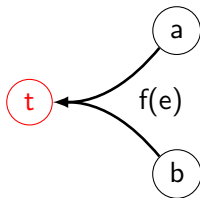
An ordered hypergraph H is a tuple $\langle N, E, t, \mathbf{R} \rangle$, where N is a finite set of nodes, E is a finite set of hyperarcs, $t \in N$ is a target node and \mathbf{R} is the set of weights. Each hyperarc $e \in E$ is a triple $e = \langle T(e), h(e), f(e) \rangle$, where $h(e) \in N$ is 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} .



Hypergraphs

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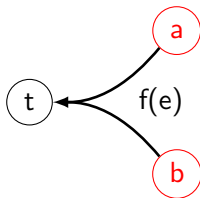
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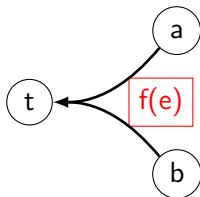
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Hypergraphs

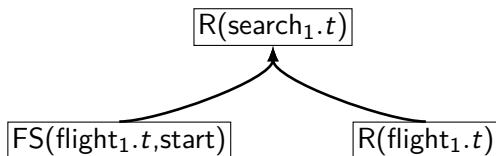
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Hypergraph Construction

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

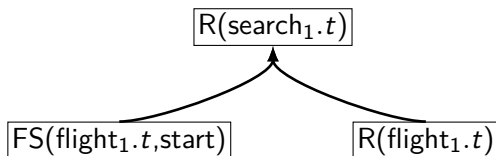


$$f(e) = f(\text{FS}_{5,7}(\text{flight}_1.t, \text{start})) \otimes f(\text{R}_{7,9}(\text{flight}_1.t)) \otimes w(\text{R}(\text{search}_1.t) \rightarrow \text{FS}(\text{flight}_1, \text{start}) \text{R}(\text{flight}_1.t))$$

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

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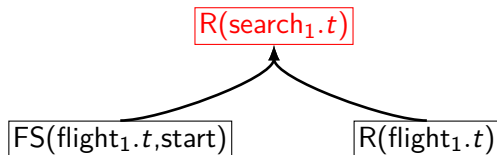


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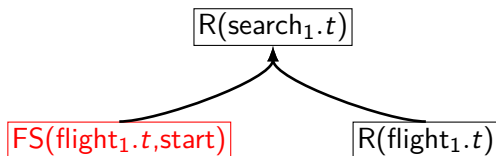


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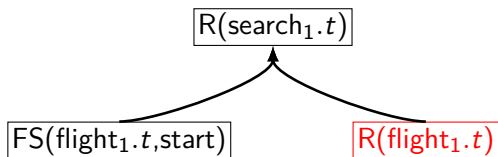


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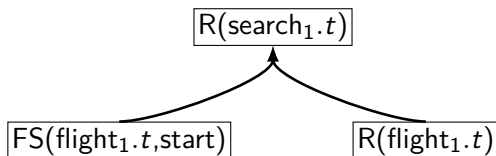


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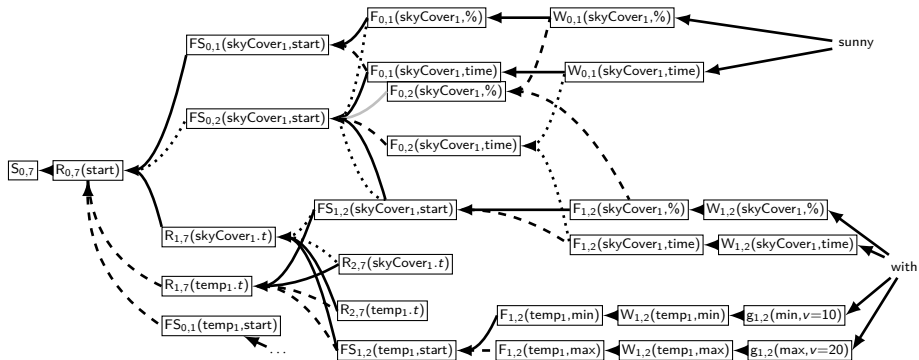
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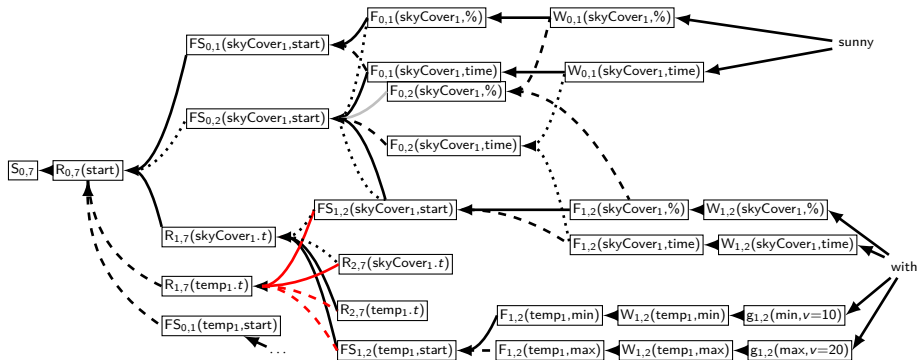
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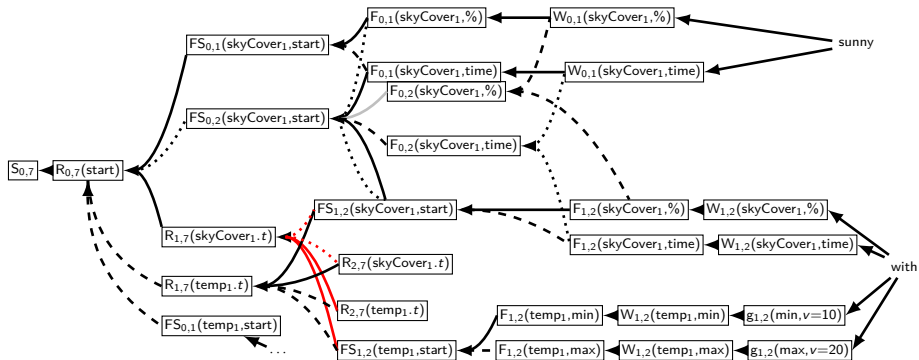
Hypergraph Example



Hypergraph Example



Hypergraph Example



Determining Text Length

- Train a linear regression model
- Idea: The more records and fields that have values in the database → 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