Unsupervised Concept-to-text Generation with Hypergraphs

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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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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

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.

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Flight

direction	**from**	**to**
oneway	edinburgh	montreal

Day

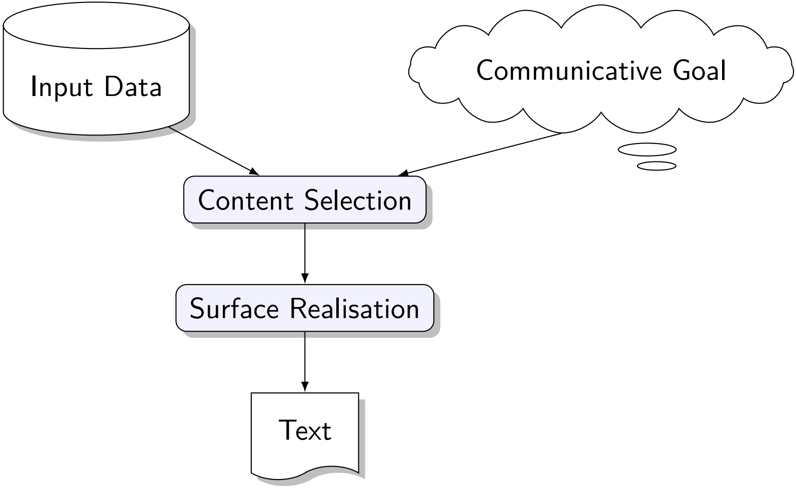
day	**dep/ar/ret**
saturday	departure

Search

of	**type**	**what**
fare	argmin	flight

Show me the cheapest one way flights
from Edinburgh to Montreal leaving on Saturday

Traditional NLG Pipeline



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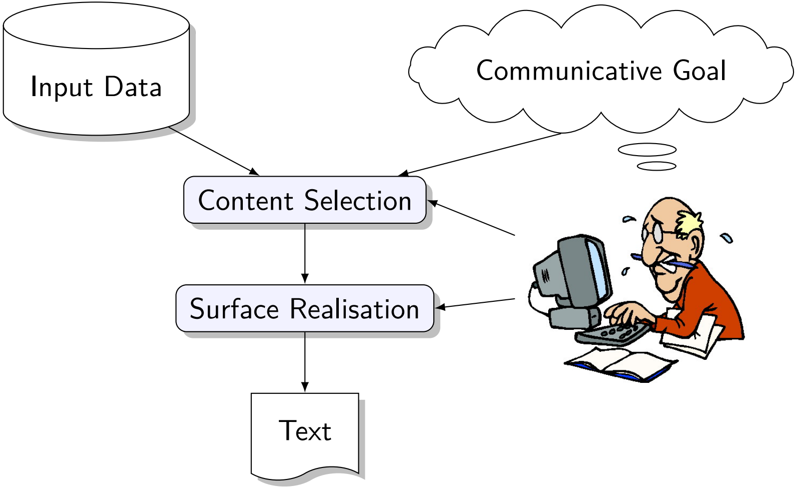

Our Approach

Temperature

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

Cloud Sky Cover

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

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Key idea: recast generation as a parsing problem

1. Describe the structure of the input with a PCFG
2. Convert PCFG to a hypergraph
3. Goal: Find the most fluent and grammatical derivation

Related Work

Angeli et al., 2010

- Unified content selection and surface realisation
- Obtain alignments from Liang et al. (2009)
- Sequence of discriminative (log-linear) local decisions (records - fields - templates)

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Our Approach

- Unsupervised generative model
- Joint content selection and surface realisation, breaks the traditional NLG pipeline
- Domain independent, trainable end-to-end system

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)

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mostly cloudy,

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Grammar Definition

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

Grammar Definition

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

1. $\mathrm{S} \rightarrow \mathrm{R}(start)$
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Grammar Definition

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

1. $\mathrm{S} \rightarrow \mathrm{R}(start)$
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Grammar Definition

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

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Grammar Definition

$\mathrm{W}(windDir_1, mode) \rightarrow \text{southeast}$

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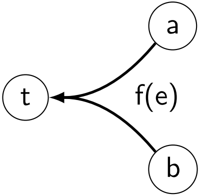
Hypergraphs

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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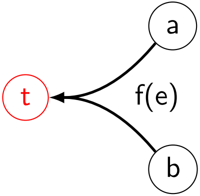

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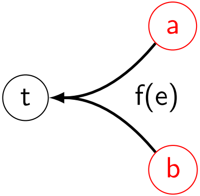

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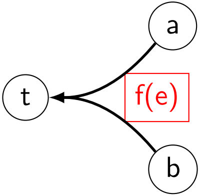
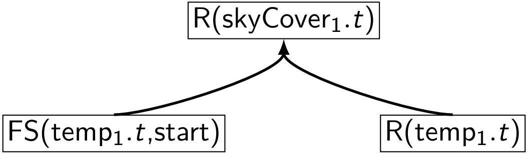


Hypergraph Construction

Map standard weighted CYK algorithm to hypergraph



$$f(e) = f(\mathrm{FS}_{1,2}(\mathrm{temp}_1.t, \mathit{start})) \otimes f(\mathrm{R}_{2,3}(\mathrm{temp}_1.t)) \otimes \\ w(\mathrm{R}(\mathrm{skyCover}_1.t) \rightarrow \mathrm{FS}(\mathrm{temp}_1, \mathit{start})\ \mathrm{R}(\mathrm{temp}_1.t))$$

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

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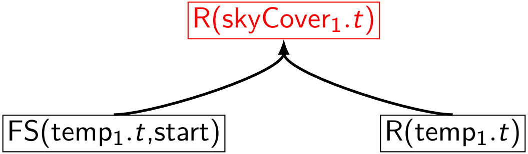

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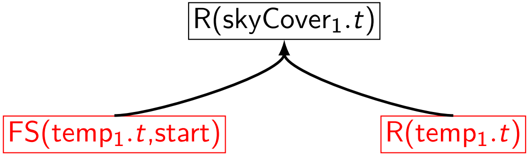

$$
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\end{aligned}
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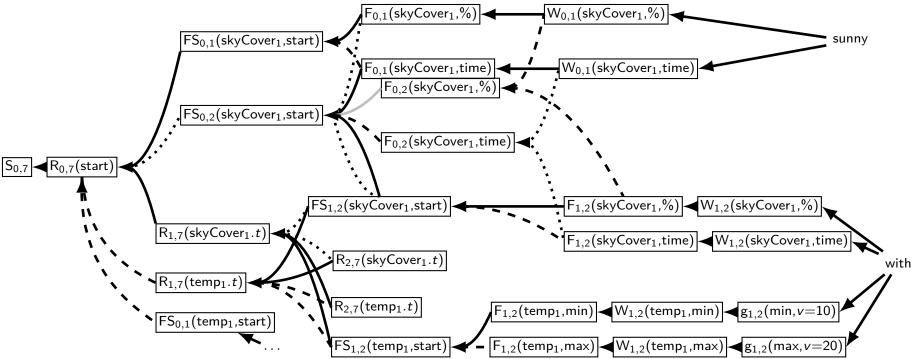
$$\mathrm{R}(r_i.t) \rightarrow \mathrm{FS}(r_j, start)\mathrm{R}(r_j.t)$$

Hypergraph Example



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

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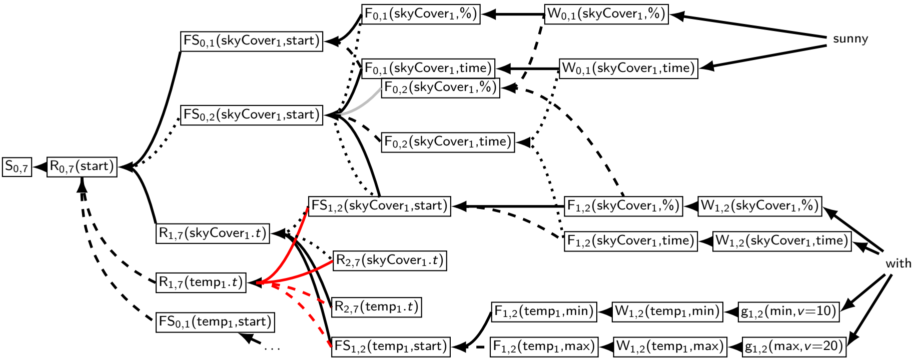

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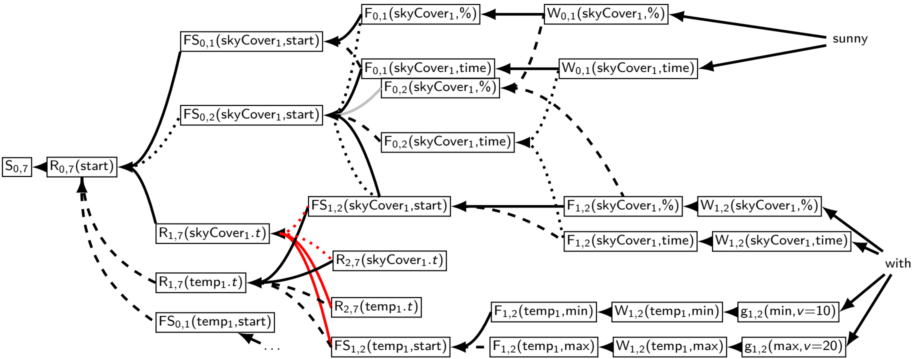


EM Training: dynamic program similar to the inside-outside algorithm

k-best Decoding

$$\arg\max_{w} P(\mathbf{w} \mid \mathbf{d}) = \arg\max_{w} P(\mathbf{w}) \cdot P(\mathbf{d} \mid \mathbf{w})$$

k-best Decoding

$$\arg\max_w P(\mathbf{w} \mid \mathbf{d}) = \arg\max_w P(\mathbf{w}) \cdot P(\mathbf{d} \mid \mathbf{w})$$

- Motivation: fluency and grammaticality
- Nodes in hypergraph $\rightarrow$ +LM items (Huang and Chiang, 2007)
  e.g. $\mathrm{R}_{2,8}(temp_1.t)^{\text{a low}\star\text{15 degrees}}$
- k-best Viterbi, cube pruning (Chiang, 2007)

k-best Decoding

Leaf nodes ϵ emit a k-best list of words

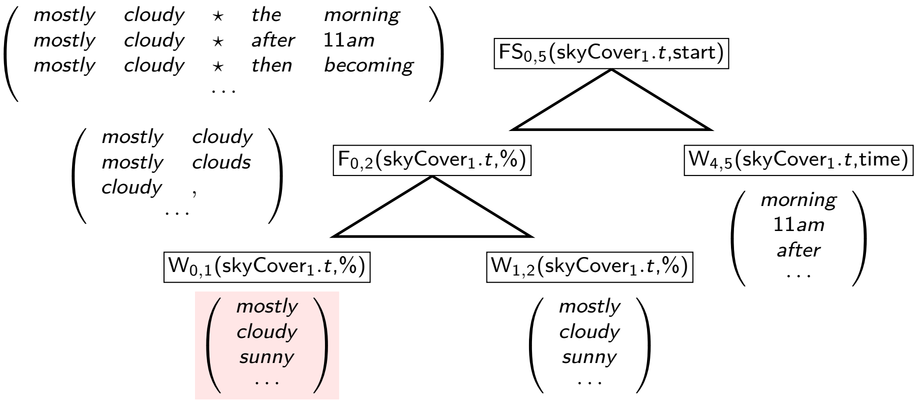
$$\boxed{\mathrm{W}_{0,1}(\mathrm{skyCover}_1.t,\%)}$$

$$\uparrow$$

$$\epsilon$$

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

k-best Decoding



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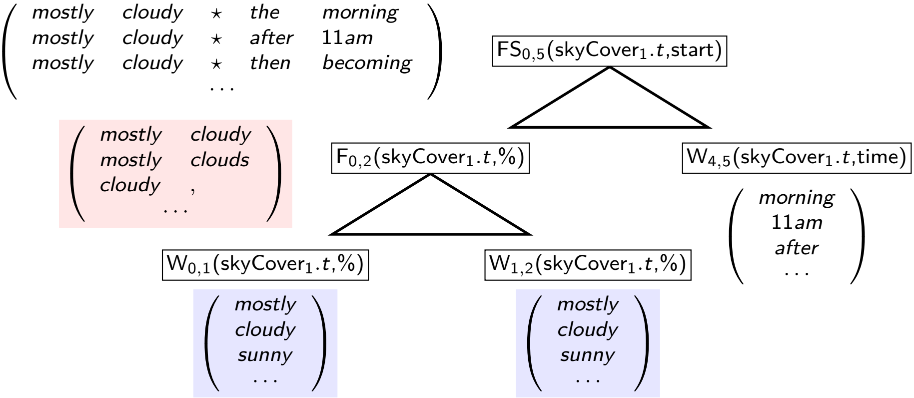

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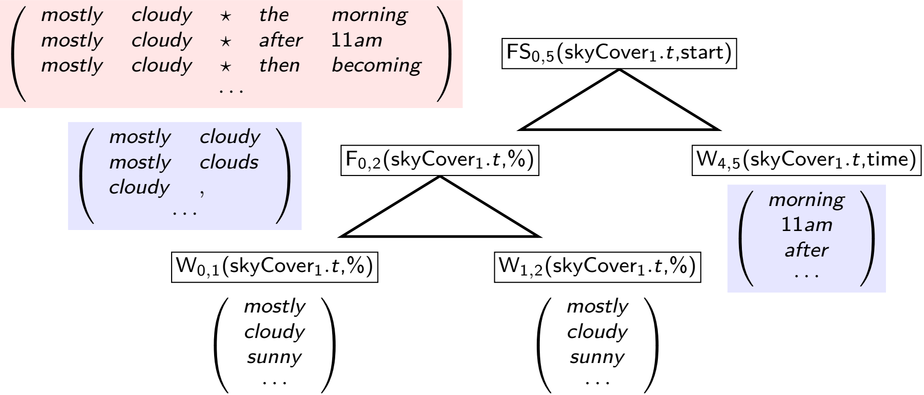

Experimental Setup

- ROBOCUP : simulated sportscasting [214 words] (Chen and Mooney, 2008)
- WEATHERGOV : weather reports [345 words] (Liang et al., 2009)
- ATIS : mapping from λ-version [927 words] (Zettlemoyer and Collins, 2007)

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- Automatic evaluation: BLEU-4
- Human evaluation (MTurk): fluency, semantic correctness

Results: Automatic Evaluation

System	RoboCup	WeatherGov	Atis
1-Best	10.79	8.64	11.85
k-Best	30.90	33.70	29.30
Angeli	28.70	38.40	26.77

- RoboCup results with fixed content selection;
- WeatherGov and Atis results with content selection and surface realization.

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Results: Human Evaluation

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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

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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
06:00-21:00	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

Conclusions

- Generation as parsing problem using the hypergraph framework
- Unsupervised end-to-end generation system
- Performance comparable to state-of-the-art
- Future work: discriminative reranking (Konstas and Lapata, 2012b)

Demo

Live Weather Forecast Generator

Cross domain

- Model trained on: `weather.gov`
- Demo runs on: `wunderground.com`
- Discrepancies (e.g. no gust information, inferred fields)

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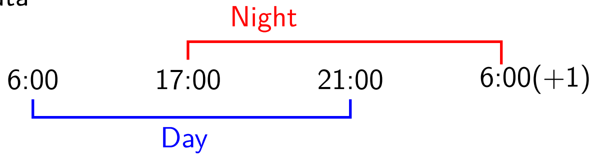
Live Data



Demo

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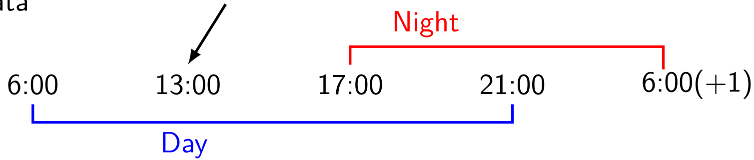

Demo

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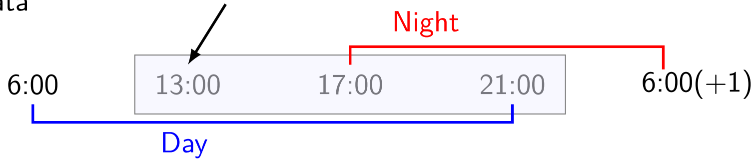

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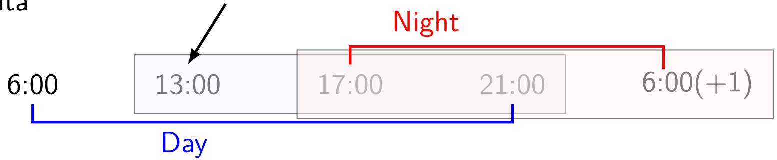

Thank you

Questions ?

Human Evaluation (Mturk)

Table 2

Category	Fields - Values			
Temperature (F)	**time:** 06.00 - 21.00	**min:** 31	**mean:** 38	**max:** 45
Wind Speed (mph)	**time:** 06.00 - 21.00	**min:** 6	**mean:** 7	**max:** 8
Wind Direction	**time:** 06.00 - 21.00	**mode:** SE		
Cloud Sky Cover (%)	**time:** 06.00 - 21.00	**percent:** 75-100		

Translation 2

MOSTLY CLOUDY , WITH A HIGH NEAR 45 . SOUTH SOUTHEAST WIND BETWEEN 6 AND 8 MPH .

Fluency ○ 1 ○ 2 ○ 3 ○ 4 ◉ 5
Semantic Correctness ○ 1 ○ 2 ○ 3 ◉ 4 ○ 5

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

Output

ROBOCUP

Input:

Pass	
From	**To**
purple10	purple11

k-BEST: **purple10 passes back to purple11**

ANGELI : purple10 passes to purple11

HUMAN: purple10 immediately passes to purple11