

Sentence Compression with Joint Structural Inference

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sentence compression

- ▶ minimize/bound lexical footprint of a sentence while keeping the most salient information

In 1967 Chapman , who had cultivated a conventional image with his ubiquitous tweed jacket and pipe , by his own later admission stunned a party attended by his friends and future Python colleagues by coming out as a homosexual .

sentence compression

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In 1967 Chapman , who had cultivated a conventional image with his ubiquitous tweed jacket and pipe , by his own later admission stunned a party attended by his friends and future Python colleagues by coming out as a homosexual .

this work

new framework for sentence compression

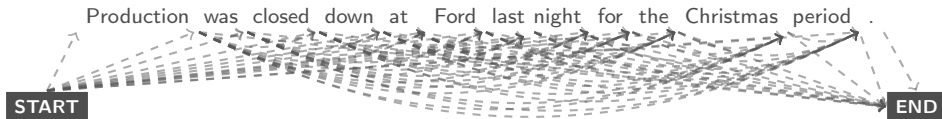
- ▶ joint inference over sequential and syntactic structure
- ▶ can exploit rich high-order linguistic features
- ▶ permits novel dependencies, reordering, etc

structural factorizations

Production was closed down at Ford last night for the Christmas period .

structural factorizations

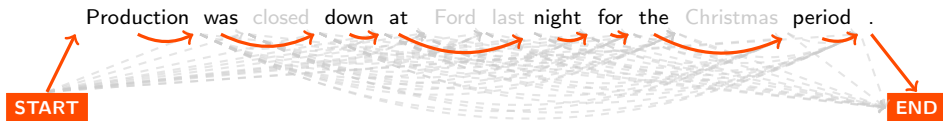
n-grams



$\langle \text{START}, \text{Production} \rangle$	$\langle \text{START}, \text{was} \rangle$	$\langle \text{START}, \text{closed} \rangle$...
$\langle \text{Production}, \text{was} \rangle$	$\langle \text{Production}, \text{closed} \rangle$	$\langle \text{Production}, \text{down} \rangle$...
$\langle \text{was}, \text{closed} \rangle$	$\langle \text{was}, \text{down} \rangle$	$\langle \text{was}, \text{at} \rangle$...
$\langle \text{closed}, \text{down} \rangle$	$\langle \text{closed}, \text{at} \rangle$	$\langle \text{closed}, \text{Ford} \rangle$...
$\langle \text{down}, \text{at} \rangle$	$\langle \text{down}, \text{Ford} \rangle$	$\langle \text{down}, \text{last} \rangle$...
$\langle \text{at}, \text{Ford} \rangle$	$\langle \text{at}, \text{last} \rangle$	$\langle \text{at}, \text{night} \rangle$...
$\langle \text{Ford}, \text{last} \rangle$	$\langle \text{Ford}, \text{night} \rangle$	$\langle \text{Ford}, \text{for} \rangle$...
$\langle \text{last}, \text{night} \rangle$	$\langle \text{last}, \text{for} \rangle$	$\langle \text{last}, \text{the} \rangle$...
⋮	⋮	⋮	

structural factorizations

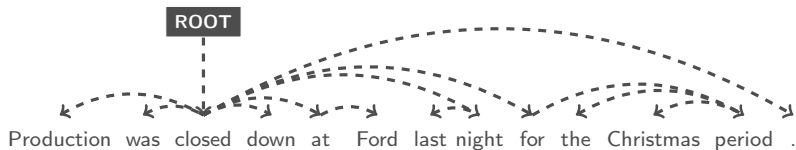
n-grams



< START, Production >	< START, was >	< START, closed >	...
< Production, was >	< Production, closed >	< Production, down >	...
< was, closed >	< was, down >	< was, at >	...
< closed, down >	< closed, at >	< closed, Ford >	...
< down, at >	< down, Ford >	< down, last >	...
< at, Ford >	< at, last >	< at, night >	...
< Ford, last >	< Ford, night >	< Ford, for >	...
< last, night >	< last, for >	< last, the >	...
⋮	⋮	⋮	

structural factorizations

dependency trees



⟨ Production ← closed ⟩

⟨ was ← closed ⟩

⟨ closed ← ROOT ⟩

⟨ down ← closed ⟩

⟨ at ← closed ⟩

⟨ Ford ← at ⟩

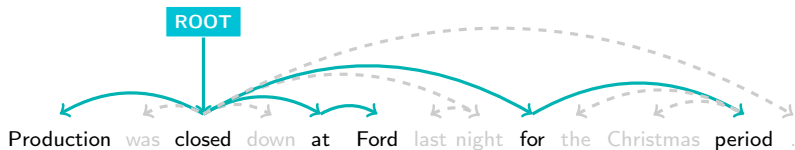
⟨ last ← night ⟩

⟨ night ← closed ⟩

⋮

structural factorizations

dependency trees



< Production ← closed >

< was ← closed >

< closed ← ROOT >

< down ← closed >

< at ← closed >

< Ford ← at >

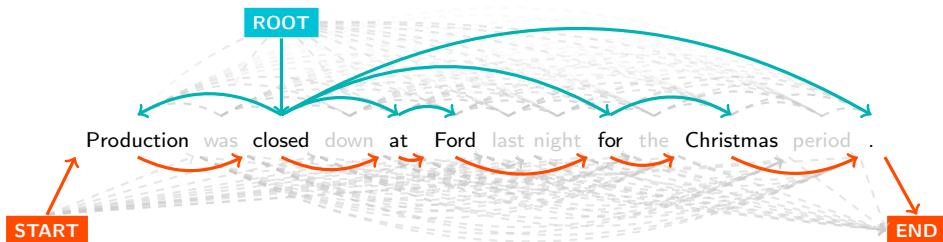
< last ← night >

< night ← closed >

⋮

structural factorizations

this work



Goal: recover tokens x , n -gram sequence y and dependency structure z

joint inference via ILP

objective

$$C = \arg \max_{\mathbf{x}, \mathbf{y}, \mathbf{z}} \underbrace{\sum_j x_j \cdot \mathbf{w}_{tok}^\top \phi(t_j)}_{\text{token score}} + \underbrace{\sum_{i,j,k} y_{ijk} \cdot \mathbf{w}_{ngr}^\top \phi(\langle t_i, t_j, t_k \rangle)}_{\text{ngram score}} + \underbrace{\sum_{i,j} z_{ij} \cdot \mathbf{w}_{dep}^\top \phi(\langle t_i, t_j \rangle)}_{\text{dep score}}$$

joint inference via ILP

objective

$$C = \arg \max_{\mathbf{x}, \mathbf{y}, \mathbf{z}} \sum_i x_i \cdot \mathbf{w}_{tok}^\top \phi(t_i) + \sum_{i,j,k} y_{ijk} \cdot \mathbf{w}_{ngr}^\top \phi(\langle t_i, t_j, t_k \rangle) + \sum_{i,j} z_{ij} \cdot \mathbf{w}_{dep}^\top \phi(\langle t_i, t_j \rangle)$$

token score

ngram score

dep score

features

- informativeness
- fluency
- fidelity
- pseudo-normalization

joint inference via ILP

constraints

- ▶ tokens \mathbf{x} , n-grams \mathbf{y} , dependencies \mathbf{z} are consistent
- ▶ $\mathbf{x}^\top \mathbf{1} < \text{compression rate}$
- ▶ \mathbf{y} forms an acyclic, connected path
- ▶ \mathbf{z} specifies a tree

} ?

commodity flow

carried in real-valued variables between pairs of tokens

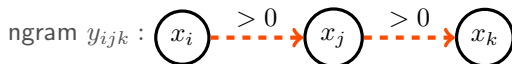
originate at a single source

⇒ guarantees connectivity

tokens consume commodity



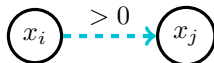
⇒ prevents cycles



ngram y_{ijk} :

adjacency
commodity

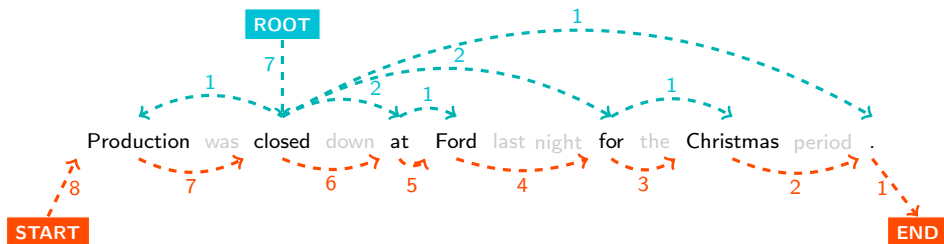
dependency z_{ij} :



dependency
commodity

commodity flow

backbone



experiments

summary

human-annotated word deletion (Clarke & Lapata, 2008)

- ▶ written news, broadcast news

5% absolute gain in $\{1,2,3,4\}$ -gram F_1 over CL08

- ▶ 13-15% relative gain in 4-gram F_1

gains in dependency F_1 against parse of gold compression

content word recall > content word precision

joint model > sequential-only

details at poster

conclusion + future work

holistic: joint production of multiple linguistic structures

expressive: generalizes over previous approaches

permits reordering, multiple input sentences

- ▶ new tasks, e.g., sentence fusion

richer dependency structure

- ▶ branching fertility, directionality, range

</talk>