An extractive supervised two-stage method for sentence compression

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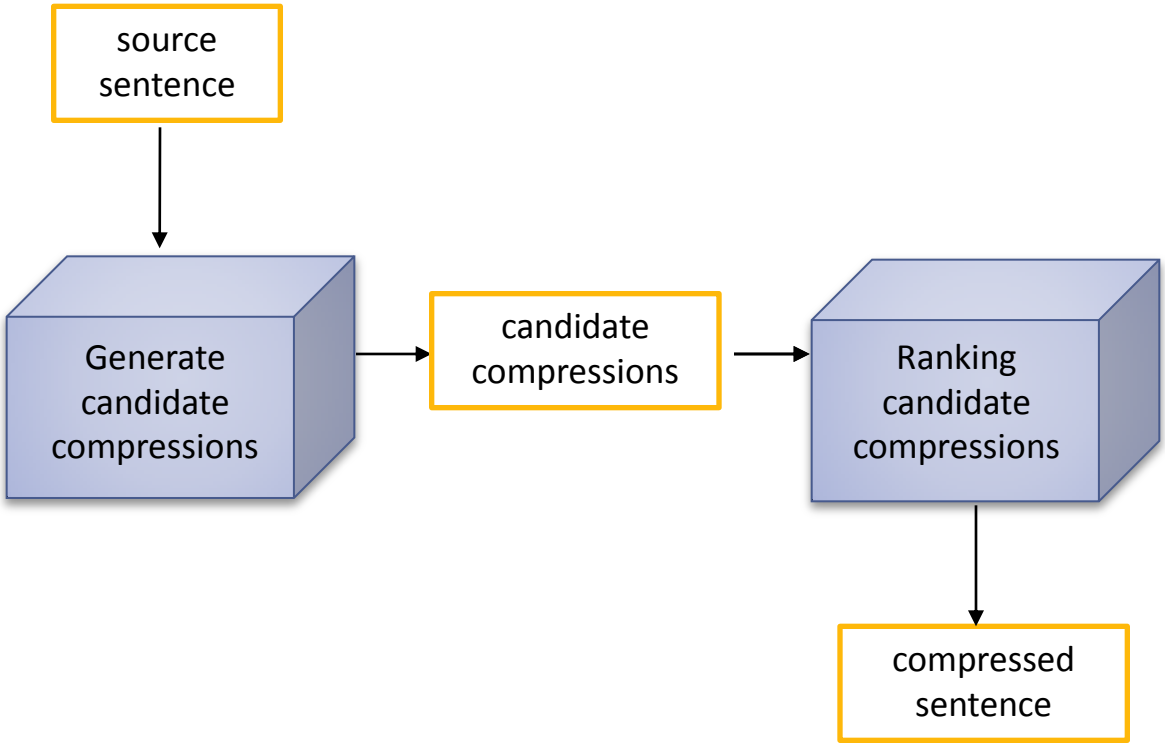
Introduction

- **Sentence compression:** produce a shorter form of a sentence, which is grammatical and retains the most important information.
- **Example:**
  - **source:** *Then last week a second note, in the same handwriting, informed Mrs Allan that the search was on the wrong side of the bridge.*
  - **compression:** *Last week a second note informed Mrs Allan the search was on the wrong side of the bridge.*
- **Examples of applications of sentence compression:**
  - text summarization
  - displaying texts on small screens
- **Extractive compression:** Only word deletions are permitted.

Our Approach

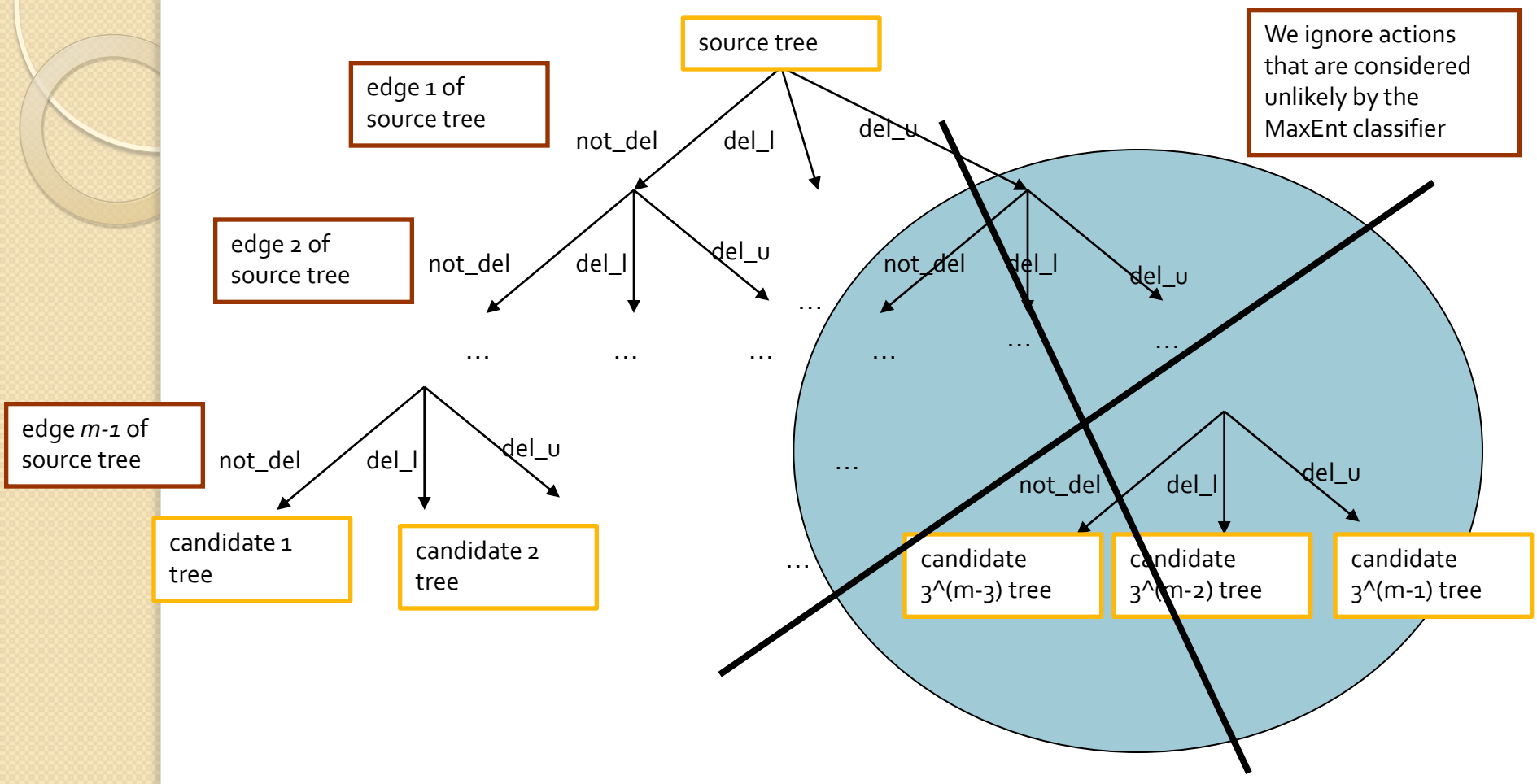
- Our algorithm compresses sentences in two stages.



Generating candidate compressions

- **Generate candidates** by **deleting edges** of the dependency tree of the source sentence.
  - For every **edge** there are **3 possible actions** leading to 3 different candidates**:**
    - **Retain** the edge (not_del).
    - **Delete** it along with the **subtree** (del_l).
    - **Delete** it along with the **uptree** (del_u).
  - Sentence with m words → at most 3^(m-1) possible candidate compressions.
- In practice we generate fewer candidates:
  - If we delete an edge along with its subtree, then there are no separate actions for the subtree's edges.
  - If an action has **low probability** (as judged by a MaxEnt classifier, next slide), we don't use in any of the candidates.

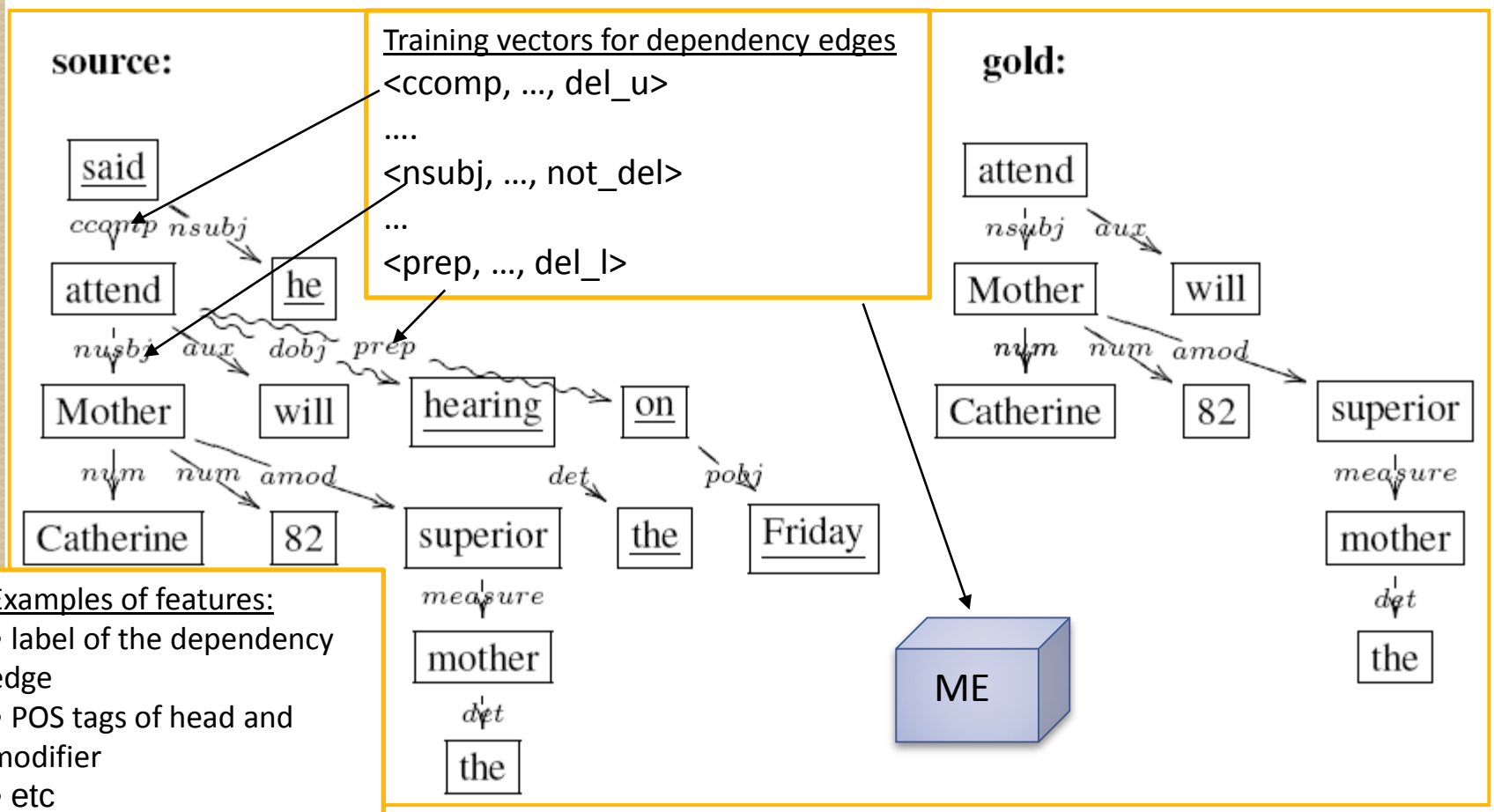
Generating candidate compressions



- We consider the edges in a top-down DFS manner.

Training the MaxEnt classifier

- Learning probabilities for actions:
  - We use a MaxEnt (ME) classifier trained on pairs of source and compressed (gold) dependency trees.



Ranking with linear combination

- We need a function $F(c_i|s)$ that will rank the candidate compressions.
  - c_i: candidate i
  - s: source
- **1st ranker we tried:** Linear combination of **grammaticality** and **importance rate** (LM-Imp model)
  - A **compression rate** penalty factor *a* is included, to bias our method towards generating shorter or longer compressions.

$$F(c_i|s) = \lambda \cdot Gramm(c_i) + (1-\lambda) \cdot \cdot ImpRate(c_i|s) - \alpha \cdot CR(c_i|s)$$

$$CR(c_i|s) = |c_i|/|s|$$

$$Gramm(c_i) = \log P_{LM}(c_i)^{1/m} = (1/m) \cdot \log(\prod_{j=1}^{m} P(w_j|w_{j-1}, w_{j-2}))$$

$$ImpRate(c_i|s) = Imp(c_i)/Imp(s)$$

$$Imp(\xi) = \sum_{w_i \in \xi} tf(w_i) \cdot idf(w_i)$$

Ranking with SVR

- **2nd ranker we tried:** Support Vector Regression (SVR) model
- SVR models are trained using *l* training vectors $(x_1, y_1), \ldots, (x_l, y_l)$ and learn a function $f : \mathbb{R}^n \rightarrow \mathbb{R}$

$x_i \in \mathbb{R}^n$

$y_i \in \mathbb{R}$

Features (x_i):
- grammaticality
- importance rate
- average depth of deleted words
- which POS tags were deleted

Score (y_i): similarity between candidate and gold

…

n **source sentences** + their **candidates** + **gold** compressions (one gold per source)

Training vectors

Candidate 1 of source sentence 1 → <0.1, 0.34, … , 0.47, 0.8>

Candidate 2 of source sentence 1 → <0.2, 0.31, … , 0.42, 0.8>

…

Candidate n of source sentence k → <1.0, 0.44, … ,0.41, 0.5>

source sentences + their **candidates**

Testing vectors

<0.1, 0.36, … , 0.42, ?>

…

SVR

A score for each candidate

SVR's similarity measures

- **Two versions of similarity** between gold (g) and candidate (c_i):
  - **Grammatical relations overlap:**
    - *d* denotes the dependencies of a sentence
    - F1 is the F-score (β=1)
    - **SVR-F1** model
  - **Tokens accuracy and grammaticality:**
    - is the percentage of tokens of *s* that were correctly retained or removed in c_i
    - **SVR-TokAcc-LM** model

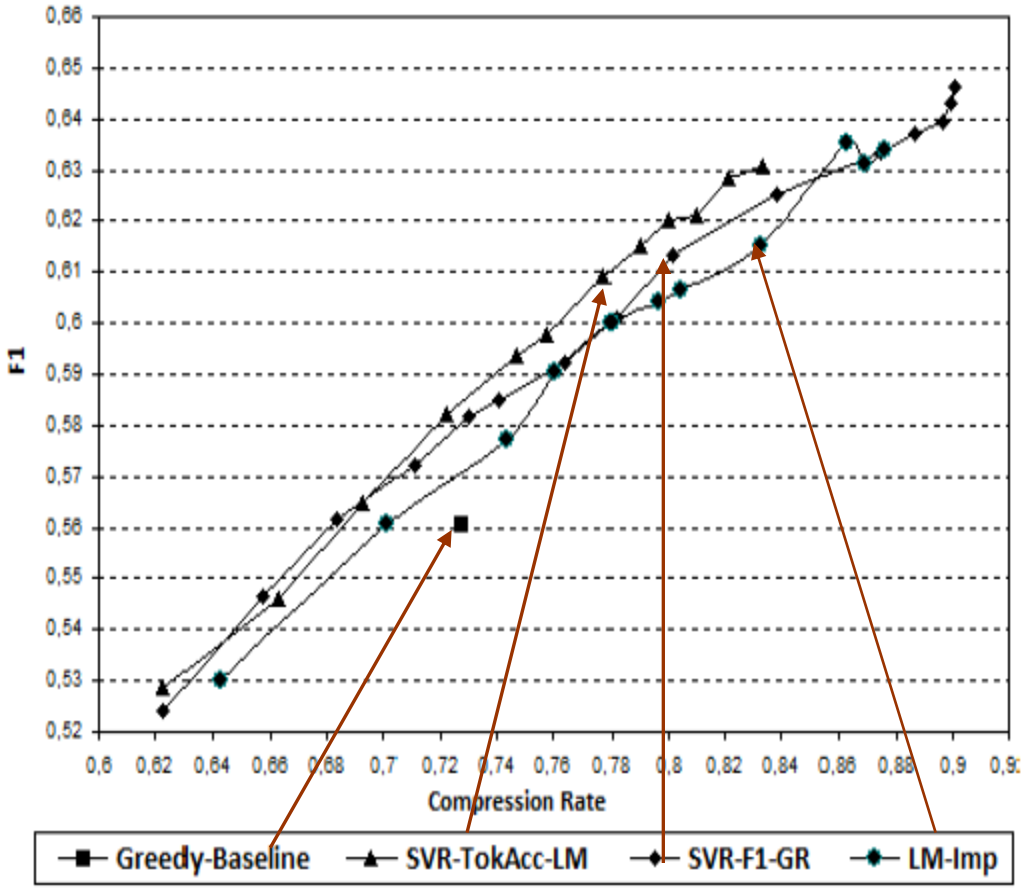
$$y_i = F_1(d(c_i)), d(g)) - \alpha \cdot CR(c_i|s)$$

$$y_i = \lambda \cdot TokAcc(c_i|s, g) + (1 - \lambda) \cdot Gramm(c_i) - \alpha \cdot CR(c_i|s)$$

Experiments

- We used Edinburgh's "written" sentence compression corpus (http://homepages.inf.ed.ac.uk/s0460084/data/)
- 3 parts:
  - training, development, and test.
- Training part used to:
  - train the MaxEnt model of Stage 1
  - train the SVR model of Stage 2.
- With $\alpha = 0$, we varied λ and selected the value that gives compression rate approximately equal to human compression.
- Then we varied parameter α (compression rate penalty factor), which is available in all models.
- ME threshold t = 0.2
  - Limits the number of candidates (< 10,000) for almost every source.
  - Tuned in preliminary experiments.

Selecting our best configuration (with automatic evaluation)



- **F1** is the avg F1-score of the **dependencies** of system compressions against gold compressions on the **development set**.
  - F1 has been shown that correlates well with human judges
- **SVR-TokAcc-LM** is the **best configuration of our system** for most compression rates.

Comparing to state-of-the-art (with human judges)

- We compared **SVR-TokAcc-LM against T3** (Cohn & Lapata 2009)
- **T3** is a **state-of-the-art** sentence compression system.
  - Best reported results on Edinburgh's "written" corpus.
- 80 source test sentences.
- **4 judges** were asked to rate **240 compressions**.
  - 80 compressions of T3, 80 compressions of our system, and 80 ld compressions.

not statistically different from T3

statistically different from T3

statistically different from both automatic systems

Similar compression rates

system	G	M	Ov	F1 (%)	CR (%)
T3	3.83	3.28	3.23	47.34	59.16
SVR	4.20	3.43	3.57	52.09	59.85
gold	4.73	4.27	4.43	100.00	78.80

Table 2: Results on 80 test sentences. G: grammaticality, M: meaning preservation, Ov: overall score, CR: compression rate, SVR: SVR-TokAcc-LM.

Conclusions

- A new sentence compression method.
  - **Candidate compressions** generated by considering **three actions per** dependency **edge** (retain, delete subtree, delete uptree).
  - A **MaxEnt** classifier **rejects unlikely actions**.
  - An **SVR** model **ranks** the candidate compressions.
  - Our method has **comparable (or better)** results to a **state-of-the-art** sentence compression system.
- Future plans:
  - Use more complex dependency tree transformations.
  - Experiment with different sizes of training data.
  - Add more features.
- Questions?