Training a Natural Language Generator from Unaligned Data

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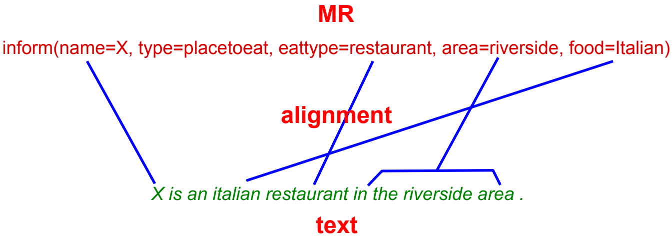

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- Our generator learns alignments jointly
  - training from pairs: **MR + sentence**

MR

inform(name=X, type=placetoeat, eattype=restaurant, area=riverside, food=Italian)

X is an italian restaurant in the riverside area .

text

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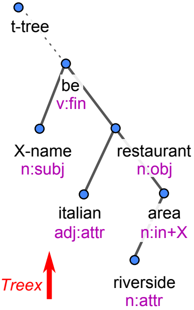
  - training from pairs: **MR + sentence**
  - with sentence planning (MR → deep syntax trees)

MR inform(name=X, type=placetoeat, eattype=restaurant, area=riverside, food=Italian)

sentence plan
deep syntax tree



automatic analysis in Treex

text *X is an italian restaurant in the riverside area .*

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inform(name=X-name, type=placetoeat, **area=centre**, eattype=restaurant, near=X-near)
*The X restaurant is **conveniently** located near X, **right in the city center**.*

inform(name=X-name, type=placetoeat, **foodtype=Chinese_takeaway**)
*X serves **Chinese food** and has a **takeaway** possibility.*

inform(name=X-name, type=placetoeat, **pricerange=cheap**)
***Prices** at X are **quite cheap**.*

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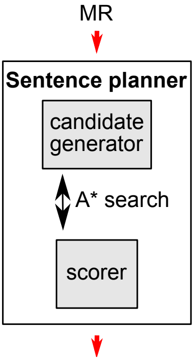

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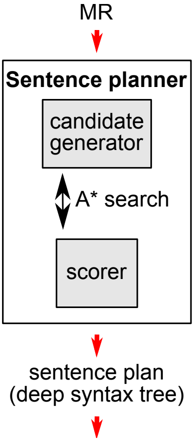

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  - reusing *Treex/TectoMT* realizer
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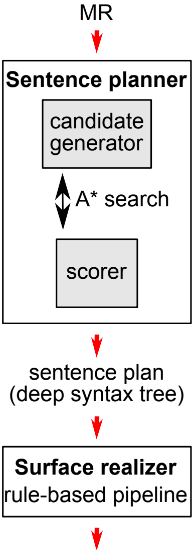

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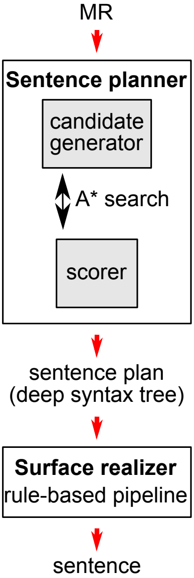

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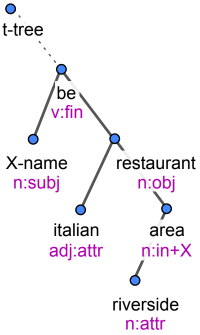

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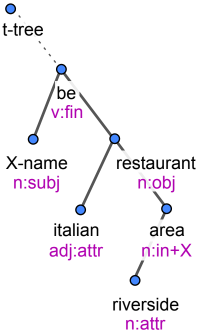

X is an Italian restaurant in the riverside area.

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- A*-style search
  - “finding the path” from empty tree to full sentence plan tree
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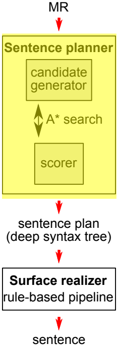

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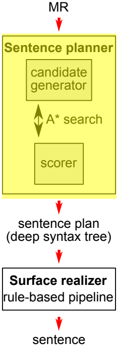

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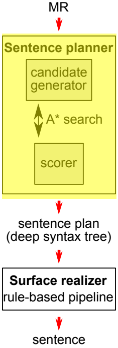

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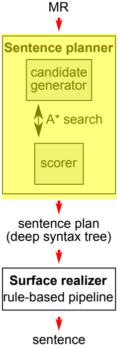
- Training data = MR + sentence plan tree pairs
  - trees obtained by automatic parsing in *Treex*



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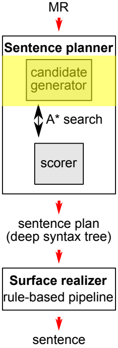

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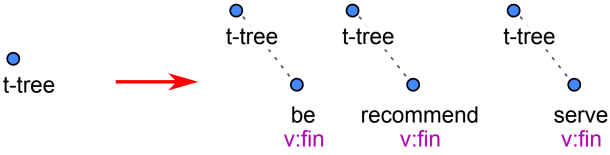

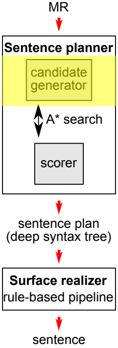

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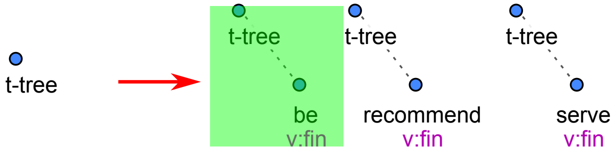

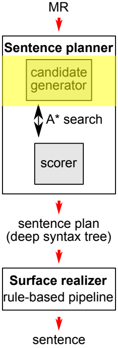

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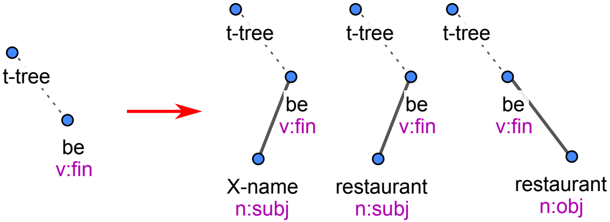

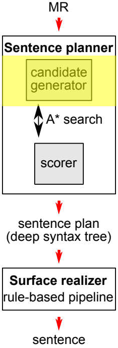

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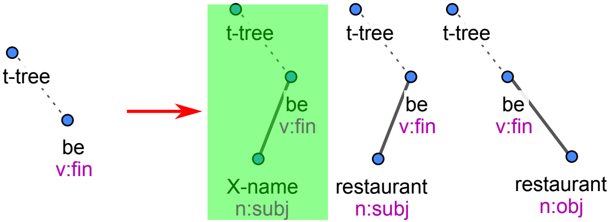

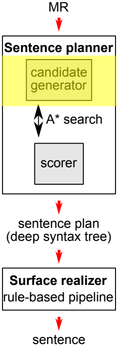

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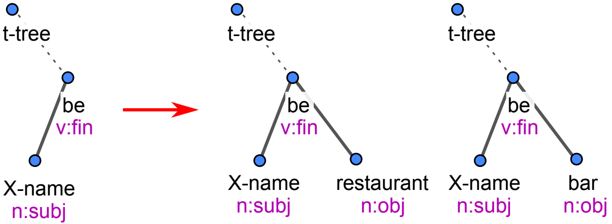

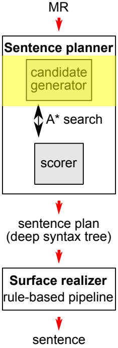

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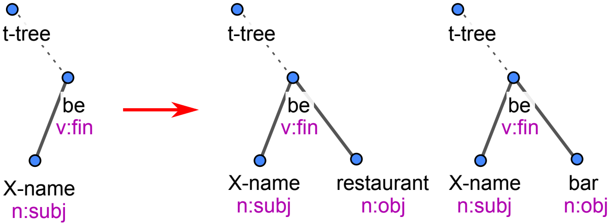
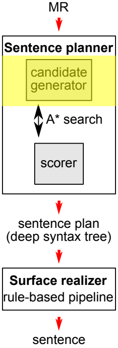


- Combinations explode even for small trees
- Limiting "possible places"
  - a few simple rules
  - based on context (elements of current MR, parent node)

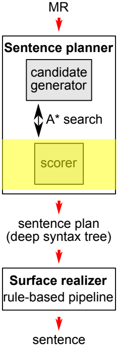


Scorer/Ranker

- a function:

  sentence plan tree + MR $\rightarrow$ real-valued score

  - describes the fitness of tree for MR



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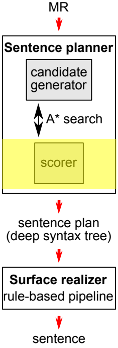
Linear perceptron scorer (Collins & Duffy, 2002)

- **score** = weights · features (from tree and MR)
  - features – elements of tree and MR
  - presence of nodes, slots, values + combination
  - tree size and shape, parent-child



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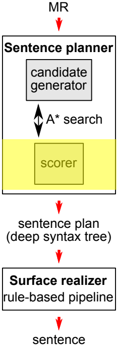

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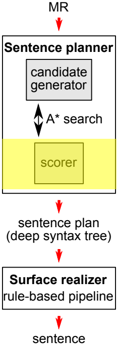
- **update** = $\alpha \cdot$ difference in features (gold$-$generated)
  - want gold to score better next time



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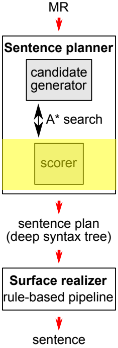

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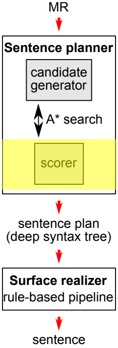

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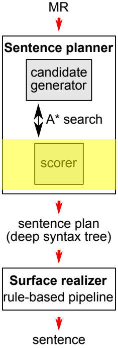

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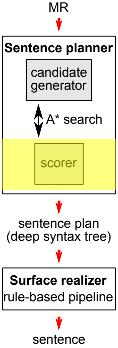
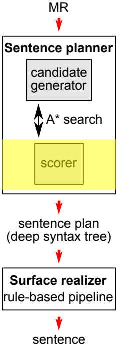
Our improvements to the scorer

- Differing tree updates
- Future promise





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- Additional perceptron update
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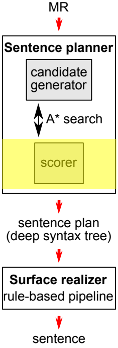

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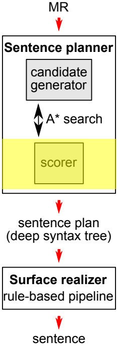

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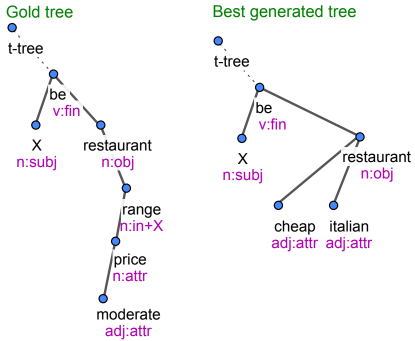

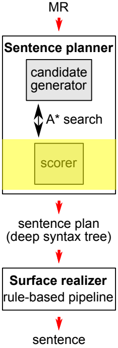

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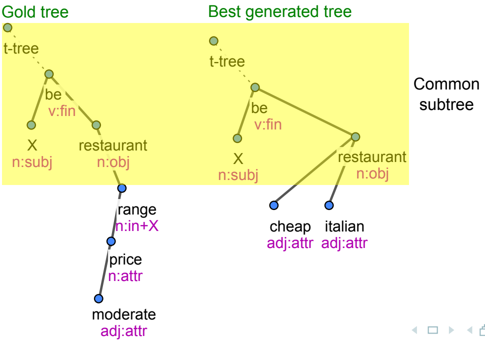

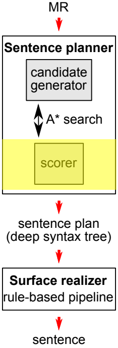

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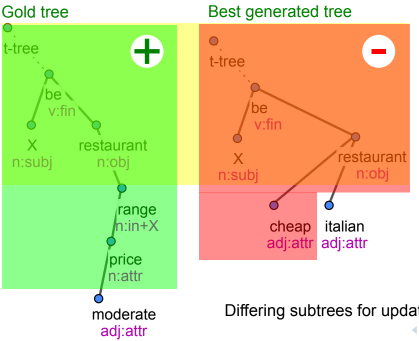
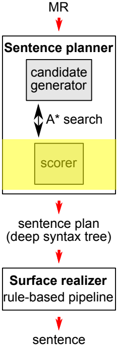


Differing subtrees for update



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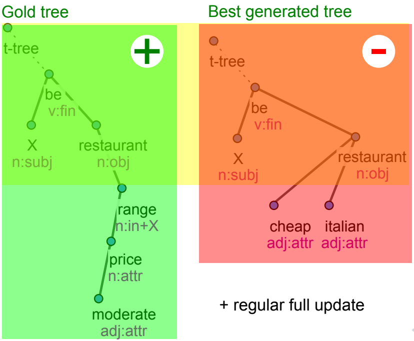
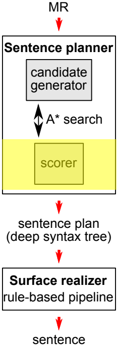


+ regular full update



Future promise estimate

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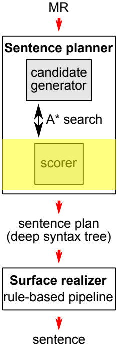

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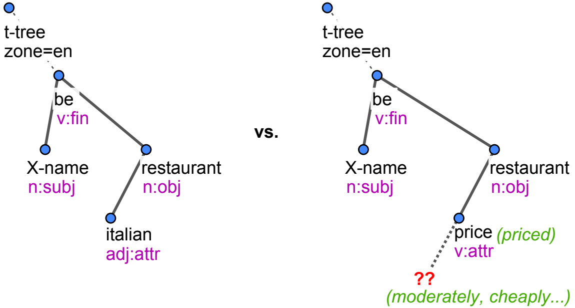
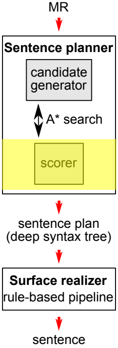
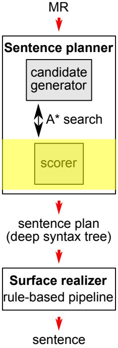
- Using the *expected number of children* of a node

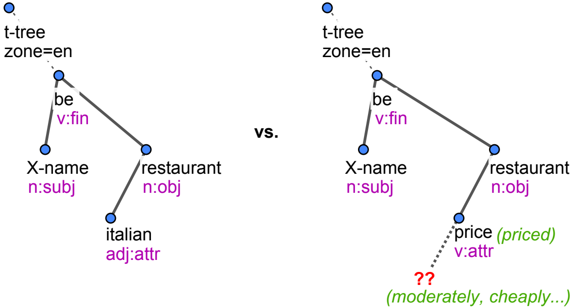






Future promise estimate

- Further score boost for incomplete trees
- Using the *expected number of children* of a node



- **Future promise**:
  "how many children are missing to meet the expectation"
  - floored at zero, summed over the whole tree
- Added to scores, used to select next expansion path

Experimental Setup

Data

- Restaurant recommendations from the *BAGEL* generator (Mairesse et al., 2010)
  - restaurant location, food type, etc.
  - 404 sentences for 202 input dialogue acts, 2 paraphrases each
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Setup	BLEU	NIST
perceptron scorer	54.24	4.643
+ differing subtree updates	58.70*	4.876
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- Overall, lower scores than Mairesse et al.'s ~ 67% BLEU
- But our problem is harder:
    - we learn alignments jointly
    - our generator has to decide when to stop (whether all required information is included)

Example Outputs

Input DA	inform(name=X-name, type=placetoeat, pricerange=moderate, eattype=restaurant)
Reference	X is a restaurant that offers moderate price range.
Generated	X is a restaurant in the moderate price range.

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- Mostly fluent and relevant
  - sometimes identical to reference, more often original
- Problems in some cases:
  - information missing / repeated / superfluous

Our NLG system – summary

- learns from unaligned MR–sentence pairs

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Conclusion

- Learning sentence planning from unaligned data is feasible
- Promising results, but lower than previous with manual alignment (Mairesse et al.)

Future work

- Refine feature set
- Replace it with a neural network
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Thank you for your attention

Contact us

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See the paper

More details there

Check out our code

`https://github.com/UFAL-DSG/tgen`

References

Collins, M. and Duffy, N. 2002. New Ranking Algorithms for Parsing and Tagging: Kernels over Discrete Structures, and the Voted Perceptron. *ACL*

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