

# Weighted posets

Learning surface order from dependency trees

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# Outline

## 1 Task

- Syntactic tree to surface realization
- Previous work

## 2 Methodology

- Weighted posets (sorted)
- Syntactic embeddings
- Graph neural network
- Example

## 3 Results

## 4 Discussion

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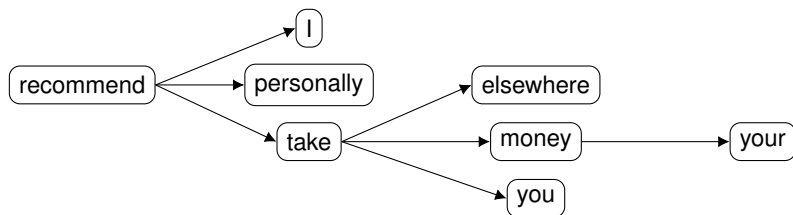
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# From syntactic tree to surface realization

## (a) syntactic tree (DAG)

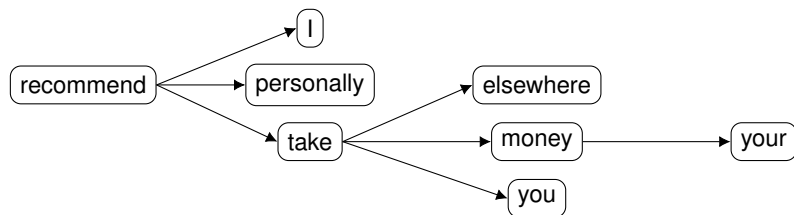


## (b) surface realization

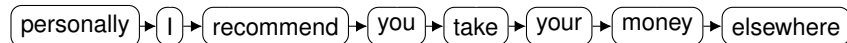


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## (a) syntactic tree (DAG)

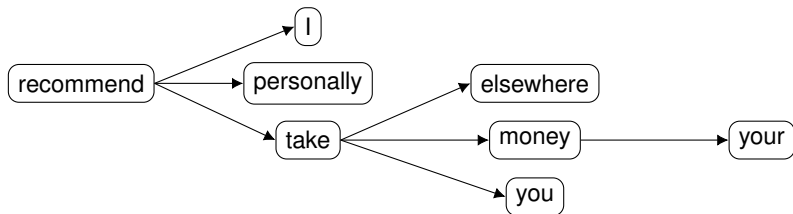


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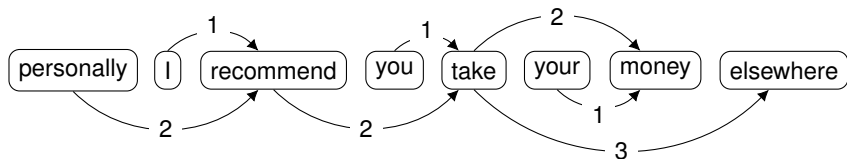


# From syntactic tree to surface realization

## (a) syntactic tree (DAG)



## (b') surface realization (poset)



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# Previous linguistic work

- Specific constituents

- ▶ demonstratives, numerals, adjectives (Greenberg, 1963)
- ▶ manner, place, time (Boisson, 1981)
- ▶ adjective order restrictions (Scott, 2002)
- ▶ complements and adjuncts

- General tree principles

- ▶ “what belongs together semantically is also placed close together” (Behaghel, 1932)
- ▶ projectivity (Marcus, 1965)
- ▶ Head Proximity (Rijkhoff, 1986)
- ▶ Early Immediate Constituents (Hawkins, 1994)
- ▶ Dependency Distance Minimization (Hudson, 1995)
- ▶ Dependency Locality Theory (Gibson, 2000)
- ▶ Minimize Domains (Hawkins, 2004)
- ▶ Uniform Information Density (Jaeger and R. Levy, 2006)



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# Previous linguistic work

- Sequential order

- ▶ “old concepts come before new ones” (Behaghel, 1932)
- ▶ “most important information first” (cf. Gundel, 1988)
- ▶ precedence relations (Gerdes and Kahane, 2001; Kahane and Lareau, 2016)
- ▶ extend DDm with info-theoretic measures (Dyer, 2018; Hahn et al., 2018)

# Previous NLG work

- Bag of words
  - ▶ “for language is not merely a bag of words but a tool with particular properties which have been fashioned in the course of its use” (Harris, 1954)
- SR '18: First Multilingual Surface Realisation Shared Task (Mille et al., 2018)
  - ▶ determine word order and inflections
  - ▶ bigram language model with binary neural-net classification (Puzikov and Gurevych, 2018)
  - ▶ seq-to-seq MT model augmented with synthetic/outside data (Elder and Hokamp, 2018)
  - ▶ sort dependents into preceding or following groups, then by syntactic category or using max entropy classifier (Castro Ferreira et al., 2018)
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- partially ordered set (poset)

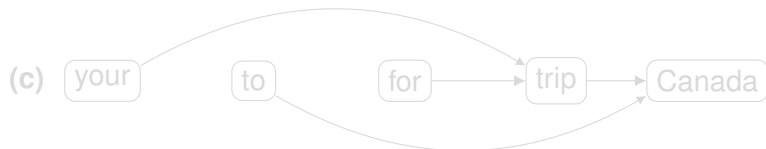
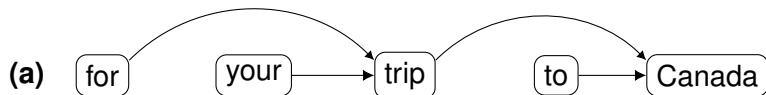
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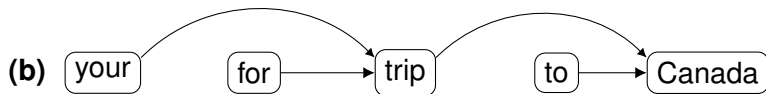
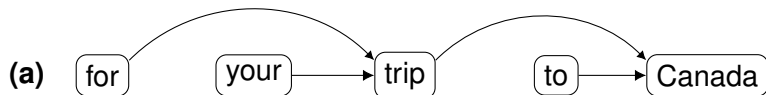
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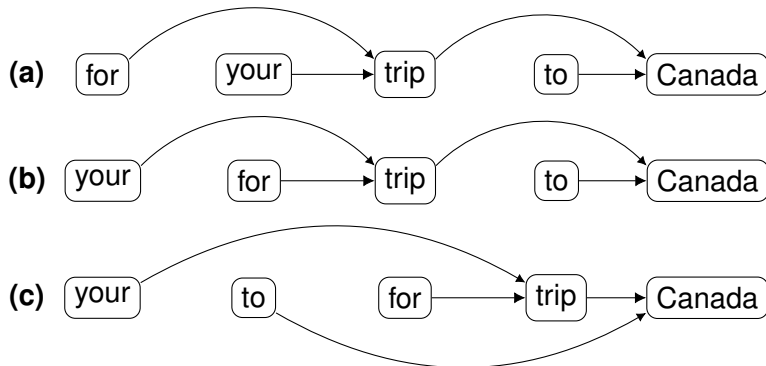
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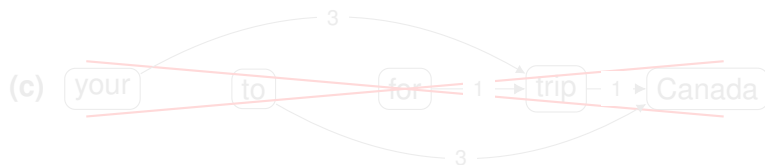
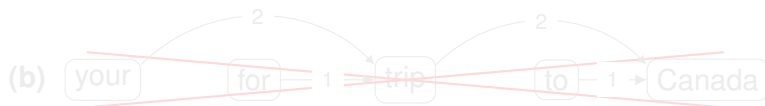
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# Weighted poset

- edge-weighted poset

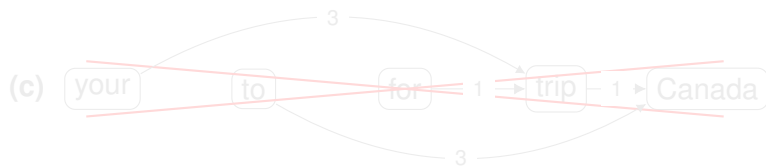
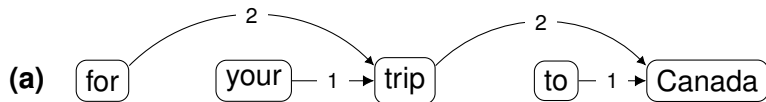
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# Weighted poset

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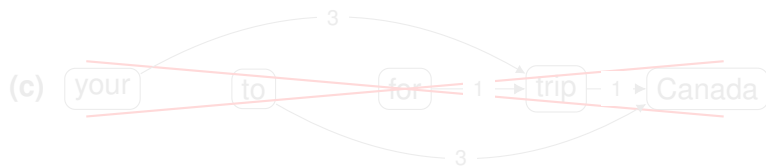
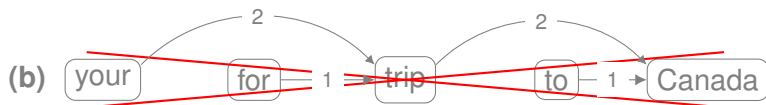
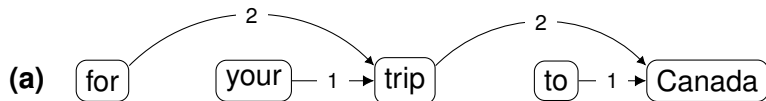
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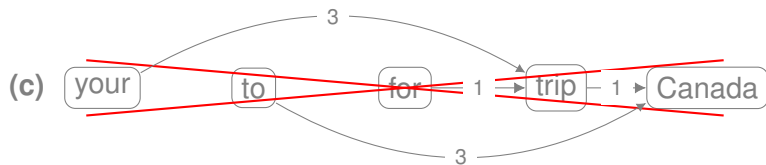
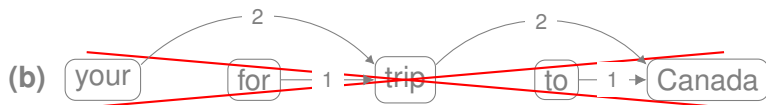
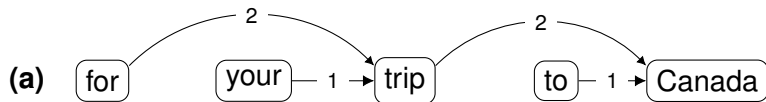




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# Topologically sorting a weighted poset

**Algorithm 1:** Given an edge-weighted *poset*, construct a total order such that nodes with smallest weights are adjacent.

```
1:  function WEIGHTED_TOPO_SORT(poset)
2:      order  $\leftarrow \emptyset$                                  $\triangleright$  empty directed graph to hold totally ordered set
3:      for (u, v,  $w_{uv}$ )  $\in$  poset do
4:           $w_{sum} \leftarrow 0$                                 $\triangleright$  a sum of traversed weights
5:          if u  $\in$  order then
6:              while  $w_{uv} > w_{sum}$  do                        $\triangleright$  traverse successors of u
7:                  s  $\leftarrow$  order.u.successor
8:                   $w_{us} \leftarrow$  order[u][s].weight
9:                   $w_{sum} \leftarrow w_{sum} + w_{us}$ 
10:                 if  $w_{uv} < w_{sum}$  then
11:                     u  $\leftarrow$  s                            $\triangleright$  u becomes its successor s
12:                  $w_{vs} \leftarrow w_{sum} - w_{uv}$               $\triangleright$   $w_{vs}$  is how much  $w_{sum}$  overshot  $w_{uv}$ 
13:                 order.UPDATE_EDGE(u, s, _)  $\leftarrow$        $\triangleright$  change existing (u, s)...
14:                     [(u, v,  $w_{us} - w_{vs}$ ), (v, s,  $w_{vs}$ )]  $\triangleright$  ... to (u, v) and (v, s) and update weights
15:             else if v  $\in$  order then
16:                 while  $w_{uv} > w_{sum}$  do                        $\triangleright$  traverse predecessors of v
17:                     p  $\leftarrow$  order.v.predecessor
18:                      $w_{pv} \leftarrow$  order[p][v].weight
19:                      $w_{sum} \leftarrow w_{sum} + w_{pv}$ 
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25:             else
26:                 order.ADD_EDGE(u, v,  $w_{uv}$ )
27:  return TOPO_SORT(order)                                 $\triangleright$  return topological sort of order graph
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# Syntactic embeddings

- **Distributional hypothesis**
  - ▶ “you shall know a word by the company it keeps” (Firth, 1957)
- Represent words as dense vectors (via NN)
  - ▶ dancing [0.43 1.91 -0.22 0.95 -0.89 ...]
  - ▶ similar words have cosine-similar vectors
- Context
  - ▶ linear (continuous bag-of-words) – word2vec (Mikolov et al., 2013)
    - ▶ dancing similar to singing, dance, dances, dancers
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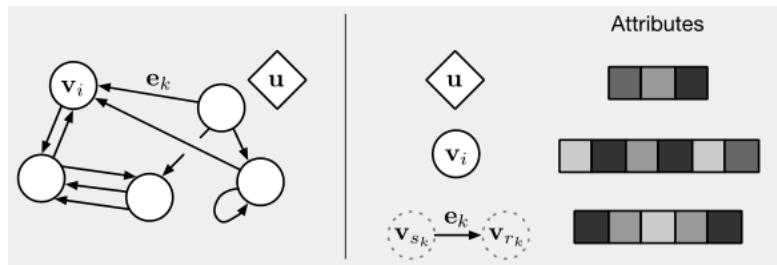
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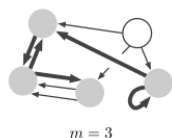
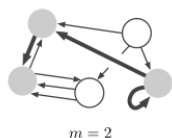
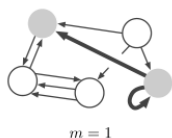
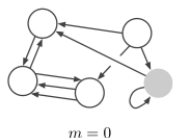
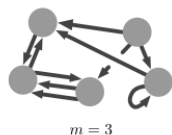
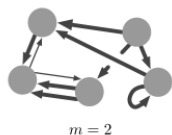
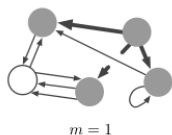
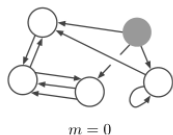
# Graph neural network (GNN)

- Graph Nets (GN) framework (Battaglia et al., 2018)



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- Graph Nets (GN) framework (Battaglia et al., 2018)
- Message-passing neural network (MPNN) (Gilmer et al., 2017)
- Spatial-based graph convolutions and pooling (Wu et al., 2019)



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## Example - word2vecf

### (a) [input] conllu file (abridged)

9	for	for	ADP	11	case
10	your	you	PRON	11	nmod:poss
11	trip	trip	NOUN	3	obl
12	to	to	ADP	13	case
13	Canada	Canada	PROPN	11	nmod

### (b) [output] syntactic embeddings

for   ADP   case	[1.69	-0.51	...]
your   PRON   nmod:poss	[0.92	-0.61	...]
trip   NOUN   obl	[0.17	-0.11	...]
to   ADP   case	[1.24	-0.59	...]
canada   PROPN   nmod	[0.05	-0.05	...]
ADP   case	[0.12	-0.80	...]
ADP	[0.10	-0.07	...]

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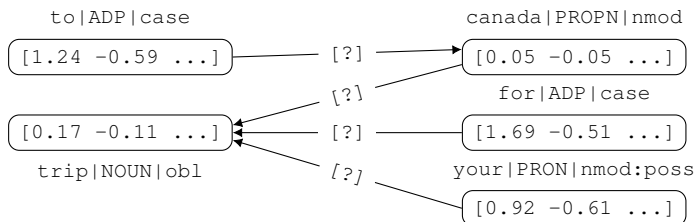
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13	Canada	Canada	PROPN	11	nmod

### (b) [output] syntactic embeddings

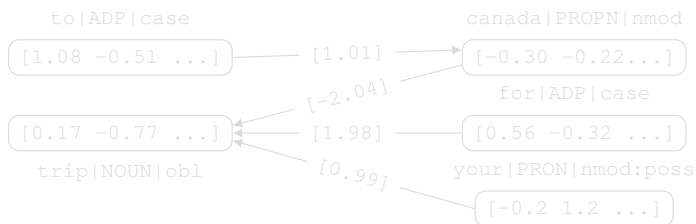
for   ADP   case	[1.69	-0.51	...]
your   PRON   nmod:poss	[0.92	-0.61	...]
trip   NOUN   obl	[0.17	-0.11	...]
to   ADP   case	[1.24	-0.59	...]
canada   PROPN   nmod	[0.05	-0.05	...]
ADP   case	[0.12	-0.80	...]
ADP	[0.10	-0.07	...]

# Example - GNN

## (c) [input] directed networkx graph of dependency tree

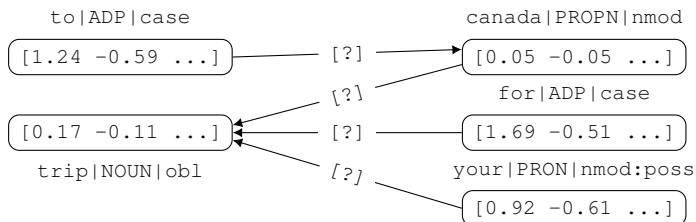


## (d) [output] directed graph with learned edge attributes

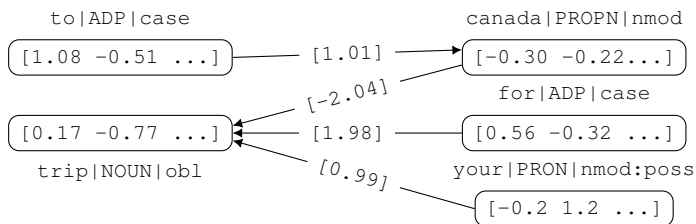


# Example - GNN

## (c) [input] directed networkx graph of dependency tree



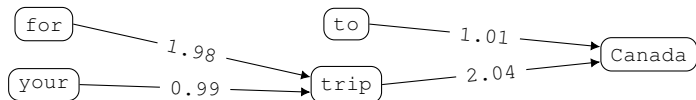
## (d) [output] directed graph with learned edge attributes



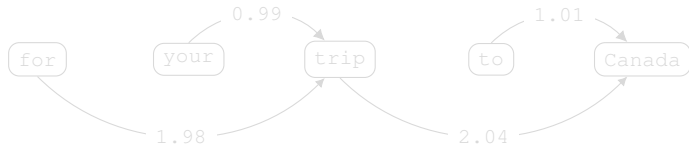


# Example - topological sort

**(e)** *[input] edge-weighted poset*

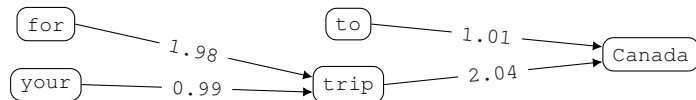


**(f)** *[output] topological sort*

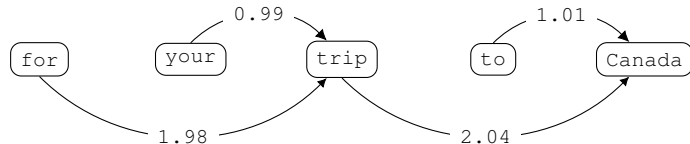


# Example - topological sort

**(e)** [input] edge-weighted poset



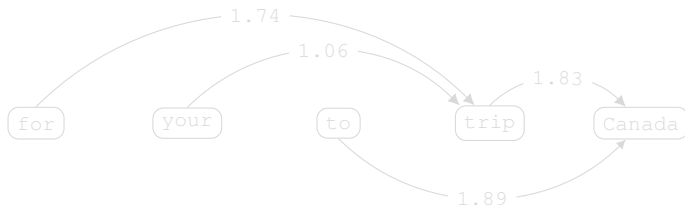
**(f)** [output] topological sort



# Baseline

- Average dependency distance

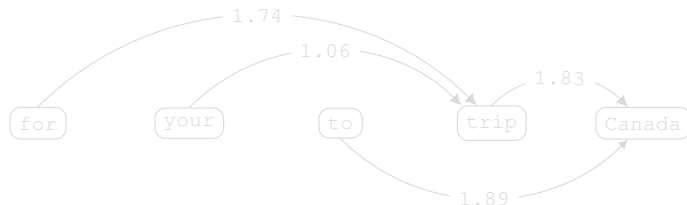
- ▶ for|ADP|case <sup>1.74</sup>  $\curvearrowright$  trip|NOUN|obl
- ▶ your|PRON|nmod:poss <sup>1.06</sup>  $\curvearrowright$  trip|NOUN|obl
- ▶ trip|NOUN|obl <sup>1.83</sup>  $\curvearrowright$  PROPEN|nmod
- ▶ to|ADP|case <sup>1.89</sup>  $\curvearrowright$  PROPEN|nmod



# Baseline

- Average dependency distance

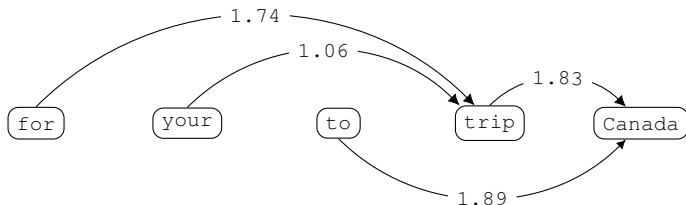
- ▶ for|ADP|case  $\prec$  <sup>1.74</sup> trip|NOUN|obl
- ▶ your|PRON|nmod:poss  $\prec$  <sup>1.06</sup> trip|NOUN|obl
- ▶ trip|NOUN|obl  $\prec$  <sup>1.83</sup> PROPN|nmod
- ▶ to|ADP|case  $\prec$  <sup>1.89</sup> PROPN|nmod



# Baseline

- Average dependency distance















- ▶ for|ADP|case  $\prec$  <sup>1.74</sup> trip|NOUN|obl
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- ▶ trip|NOUN|obl  $\prec$  <sup>1.83</sup> PROPN|nmod
- ▶ to|ADP|case  $\prec$  <sup>1.89</sup> PROPN|nmod



















# Results

SPEARMAN'S  $\rho$  [-1,1]

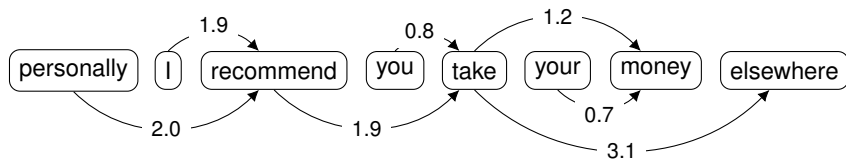
PROJECTIVITY [0,1]

	AVG		GNN	AVG		GNN	UD
Afrikaans	0.707		<b>0.773</b>	0.530		<b>0.650</b>	0.939
Armenian	0.628		<b>0.672</b>	0.413		<b>0.585</b>	0.987
Czech	0.665		0.659	0.359		<b>0.469</b>	0.982
English	0.634		<b>0.775</b>	0.496		<b>0.680</b>	0.995
French	0.677		<b>0.729</b>	0.531		<b>0.669</b>	0.998
Greek	0.731		<b>0.754</b>	0.503		<b>0.651</b>	0.996
Hungarian	0.635		0.609	0.440		<b>0.598</b>	0.969

# Results

	SPEARMAN'S $\rho$ [-1,1]			PROJECTIVITY [0,1]			
	AVG		GNN	AVG		GNN	UD
Irish	0.674		<b>0.753</b>	0.461		<b>0.603</b>	0.978
Italian	0.657		<b>0.796</b>	0.482		<b>0.651</b>	0.996
Latin	0.614		0.582	0.613		<b>0.729</b>	0.855
Maltese	0.729		<b>0.750</b>	0.498		<b>0.682</b>	0.995
Slovenian	0.549		<b>0.567</b>	0.663		<b>0.798</b>	0.967
Telugu	0.916		<b>0.931</b>	0.925		<b>0.971</b>	0.997
Uyghur	0.728		0.727	0.629		<b>0.762</b>	0.976

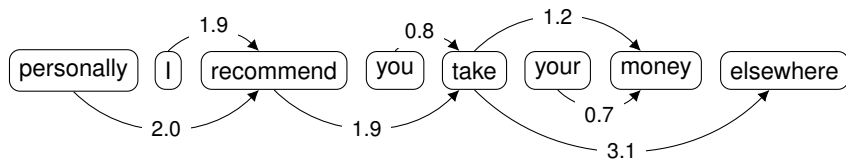
# Discussion



- Engineering
  - ▶ not E2E, but using ML to address parts of problem
  - ▶ useful data structure for representing surface realizations
  - ▶ entirely within dependency framework
- What is GNN learning?
  - ▶ relative individual dependency-distance **tolerances** ...
  - ▶ based on **context** of words (embeddings) and structure (MPNN)
- Emergent projectivity rate
  - ▶ no baked-in notion or representation of projectivity
  - ▶ rate reflects (approaches) that of training data

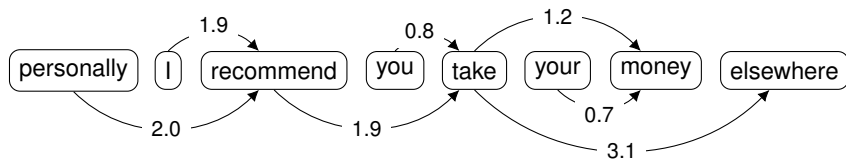


# Discussion



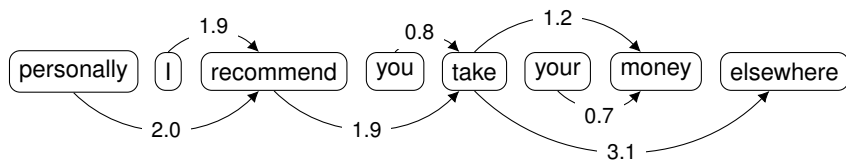
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# Future study

- improve design of GNN
- customize hyperparameters based on corpus
- use newer embedding frameworks
- develop/find efficient algorithm for sorting weighted posets
- apply weighted posets to study graph-theoretic measures

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Thank you!

**Weighted posets**  
**Learning surface order from dependency trees**

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