

Towards an omnilingual model for solving morphological analogies

Safa AlSaidi, Amandine Decker, Stephanie Monteiro

M2 — Software Project



- 1 Introduction
- 2 Project's objective
- 3 Dataset preprocessing
- 4 Neural models
- 5 Results
- 6 Software demo
- 7 Conclusion and perspectives

What is an analogy?

Analogy

$$A : B :: C : D$$

"A is to B as C is to D"

Same relation between the pair A and B and the pair C and D

Order

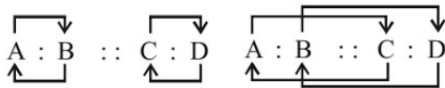


Figure: Symmetry and central permutation

Mathematical examples

- $1 : 2 :: 5 : 6 \leftrightarrow 1 - 2 = 5 - 6$ (Arithmetic)
- $1 : 2 :: 2 : 4 \leftrightarrow 1/2 = 2/4$ (Geometric)

What is morphology?

Morphemes

- Root (or base)
- Affixes: prefixes, suffixes

Prefixation

inactive_A → in + active_A

disappear_V → dis + appear_V

Suffixation

useful_A → use_N + ful

reads_V → read_V + s

Prefixation & suffixation

unconsciousness_N → un + conscious_A + ness

What is a morphological analogy?

Example: “cat is to cat**s** as star is to star**s**”

Comparison in terms of the presence and absence of affixes to determine the validity and correctness of analogies

Typical tasks

1 Classification

Valid examples

"cat": "cats" :: "apple": "apples"

"cat": "apple" :: "cats": "apples"

Invalid examples

"cat": "apples" :: "cats": "apple"

"cat": "cat" :: "apple": "apples"

2 Solving Analogies

- ▶ when one word is missing/unknown
- ▶ "cat": "cats" :: "apple": $X \rightarrow X = \text{"apples"}$

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Solving multilingual morphological analogies

- Analogy solving task based on transfer

$$A : B :: C : X \xrightarrow{X=?} A : B :: C : D$$

e.g. *dog : dogs :: chat : X* \rightarrow *chats*

- ▶ Input: A and B in language 1, C in language 2
- ▶ Output: D in language 2
- ▶ Same transformation for A, B and C, D

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Datasets

SIGMORPHON 2016 [Cotterell et al., 2016] and the Japanese Bigger Analogy Test Set [Karpinska et al., 2018].

- contain triples (lemma, target features, target word)
- analogies are generated based on triples sharing the same features ($F = F'$).

$$\langle A, F, B \rangle, \langle A', F', B' \rangle$$

Valid examples

```
cat      pos=N, num=PL   cats
apple    pos=N, num=PL   apples
cat:cats::apple:apples is valid
```

Invalid examples

```
cat      pos=N, num=PL           cats
sleep    pos=V, tense=PRS, per=3, num=SG   sleeps
cat:sleep::cats:sleeps is invalid
```

Language choice

We kept languages that shared features with other languages.

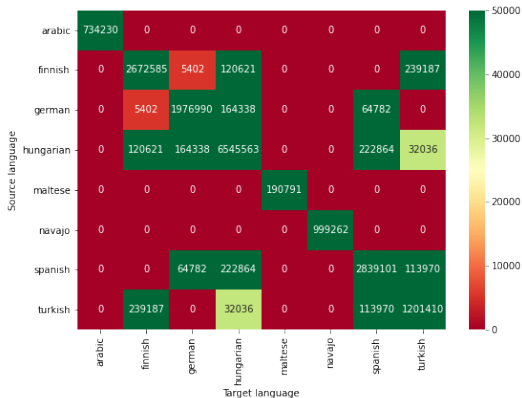
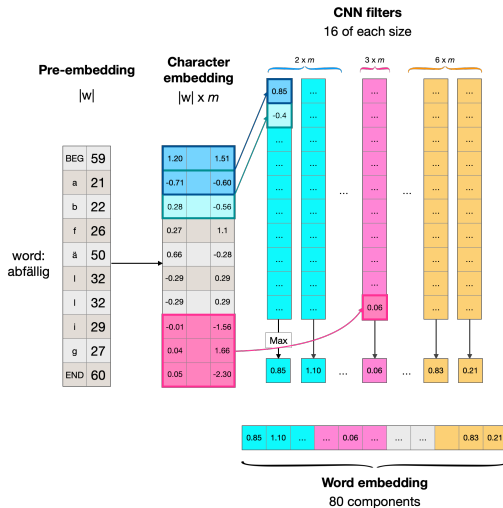


Figure: Number of possible analogies for each pair of languages

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Custom embedding model

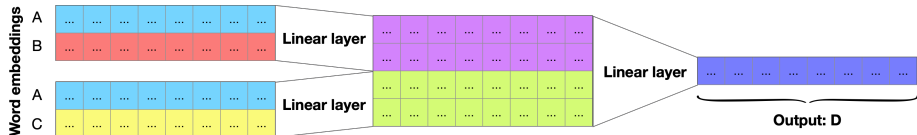


This model was inspired by [Kim et al., 2016]

Analogy solver model

$$A : B :: C : X \xrightarrow{X=?} A : B :: C : D$$

$$X = g(f_1(A, B), f_2(A, C))$$



This model was inspired by [Lim et al., 2019]

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Monolingual analogy solving models

Language	ANNr (previous) (mean \pm std.)	diff. parameters (mean \pm std.)
Arabic	77.97 \pm 16.03	61.13 \pm 0.83
Finnish	37.78 \pm 9.28	76.46 \pm 1.58
Georgian	94.66 \pm 1.13	84.67 \pm 2.78
German	86.38 \pm 0.45	88.70 \pm 0.58
Hungarian	53.83 \pm 3.12	78.72 \pm 0.53
Maltese	75.00 \pm 5.08	78.04 \pm 1.44
Navajo	31.74 \pm 0.90	45.74 \pm 0.99
Russian	75.15 \pm 0.44	72.23 \pm 0.44
Spanish	86.27 \pm 0.71	91.72 \pm 0.43
Turkish	61.95 \pm 10.86	80.37 \pm 1.00
Japanese	61.60 \pm 1.33	72.58 \pm 2.47

Table: Accuracy (in %) of the analogy solving models (10 runs for the new results, 3 for previous ones)

Omnilingual analogy solving model

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	61.85 ± 1.79	3.22 ± 1.73	28.58 ± 2.69	/	55.23 ± 3.85
German	3.15 ± 1.47	64.38 ± 1.27	66.91 ± 4.49	62.07 ± 3.58	/
Hungarian	36.26 ± 4.52	55.25 ± 1.47	73.33 ± 1.31	78.36 ± 1.33	32.00 ± 3.03
Spanish	/	61.16 ± 2.54	74.05 ± 1.77	69.38 ± 1.65	70.67 ± 4.03
Turkish	54.12 ± 1.48	/	25.38 ± 3.94	65.72 ± 6.09	52.23 ± 1.09

Table: Accuracy (in %) of 10 runs of the omnilingual analogy solver model

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Valid analogy

ANNa

[About Us](#) [Our app](#) [More about analogies](#) [More about morphology](#)

Analogies and Neural Networks

This website shows you several features of analogies. You can click on ⓘ to get more information.
Click on *Generate an example* to get a valid example, you can then solve it manually or see what our neural network proposes with *Get closest result*.
Eventually, *Get the right answer* will give you the right answer if yours was wrong.

ⓘ Source language: Hungarian

Target language: Any language

Advanced options ⌵

Transformation: Noun, accusative case, plural ⓘ

Generate an example ⓘ

Hungarian to Finnish: Noun, accusative case, plural

adomány :: adományokat :: kabardi :: kabardit

ⓘ Get closest result

Get the right answer

Shuffle the words ⓘ

Figure: Preview of our software

Invalid analogy

Analogies and Neural Networks

This website shows you several features of analogies. You can click on ⓘ to get more information. Click on *Generate an example* to get a valid example, you can then solve it manually or see what our neural network proposes with *Get closest result*. Eventually, *Get the right answer* will give you the right answer if yours was wrong.

Source language: German Target language: Finnish Advanced options ▾

Transformation: Adjective ⓘ

Adjective, accusative case, plural

Adjective, genitive case, plural

Generate an example ⓘ

German to Finnish: Adjective, accusative case, plural

aufmunternd

aufmunternde

mietteläs

mingas

ⓘ **Get closest result**

Get the right answer

Shuffle the words ⓘ

This result is not the expected one (mietteliäät).

Figure: Preview of our software

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Final Remarks

❶ What did we manage to do?

- ▶ Improve analogy solving results
- ▶ Explore bilingual analogies
- ▶ Train an omnilingual model
- ▶ Develop a software

❷ What challenges did we encounter?

- ▶ Language proximity

❸ What can be improved?

- ▶ Qualitative analysis
- ▶ Decoder
- ▶ Extend to other languages

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شكرا جزيلا




Thank you

Merci

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Obrigado

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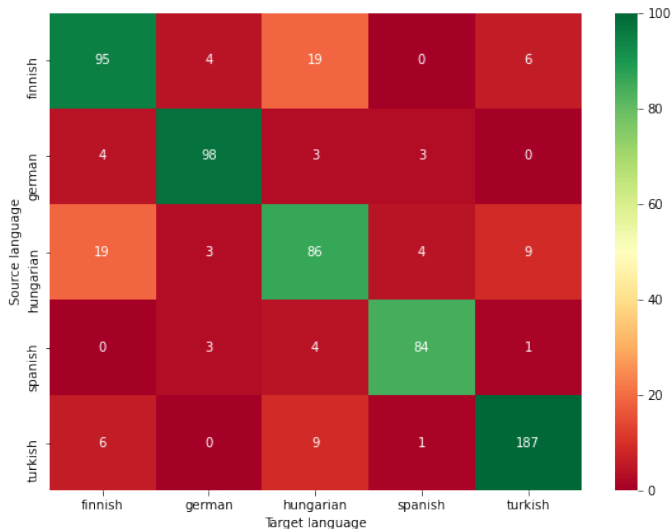
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- 1 Omnilingual model
- 2 Decoder
- 3 Bilingual models

Number of different features per languages



Omnilingual vs Bilingual

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	/	3.22±1.73	28.58±2.69	/	55.23±3.85
German	3.15±1.47	/	66.91±4.49	62.07±3.58	/
Hungarian	36.26±4.52	55.25±1.47	/	78.36±1.33	32.00±3.03
Spanish	/	61.16±2.54	74.05±1.77	/	70.67±4.03
Turkish	54.12±1.48	/	25.38±3.94	65.72±6.09	/

Table: Accuracy (in %) of 10 runs of the omnilingual analogy solving model (diff. parameters)

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	/	66.01±33.01	36.28±0.76	/	28.34±0.48
German	64.43±32.23	/	30.53±0.57	11.92±3.30	/
Hungarian	50.61±2.26	77.98±1.24	/	94.02±0.29	33.89±0.77
Spanish	/	32.42±17.01	78.99±0.13	/	40.45±1.52
Turkish	46.43±1.24	/	16.07±0.90	70.86±0.04	/

Table: Accuracy (in %) of 5 runs of the bilingual analogy solving models (diff. parameters)

Omnilingual vs Monolingual

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	61.85±1.79	3.22±1.73	28.58±2.69	/	55.23±3.85
German	3.15±1.47	64.38±1.27	66.91±4.49	62.07±3.58	/
Hungarian	36.26±4.52	55.25±1.47	73.33±1.31	78.36±1.33	32.00±3.03
Spanish	/	61.16±2.54	74.05±1.77	69.38±1.65	70.67±4.03
Turkish	54.12±1.48	/	25.38±3.94	65.72±6.09	52.23±1.09

Table: Accuracy (in %) of 10 runs of the omnilingual analogy solving model (diff. parameters)

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	76.46±1.58	39.75±2.67	80.33±1.95	/	79.89±2.43
German	94.26±0.63	88.70±0.58	70.55±2.61	70.55±2.61	/
Hungarian	43.93±3.44	85.39±1.76	78.72±0.53	85.39±1.76	40.98±3.42
Spanish	/	94.26±0.53	94.26±0.53	91.72±0.43	95.83±0.24
Turkish	64.98±2.76	/	70.74±2.23	94.03±3.70	80.37±1.00

Table: Accuracy (in %) of 10 runs of the monolingual analogy solver models (evaluated on shared features only)

Omnilingual model (diff. parameters): different training datasets

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	61.85±1.79	3.22±1.73	28.58±2.69	/	55.23±3.85
German	3.15±1.47	64.38±1.27	66.91±4.49	62.07±3.58	/
Hungarian	36.26±4.52	55.25±1.47	73.33±1.31	78.36±1.33	32.00±3.03
Spanish	/	61.16±2.54	74.05±1.77	69.38±1.65	70.67±4.03
Turkish	54.12±1.48	/	25.38±3.94	65.72±6.09	52.23±1.09

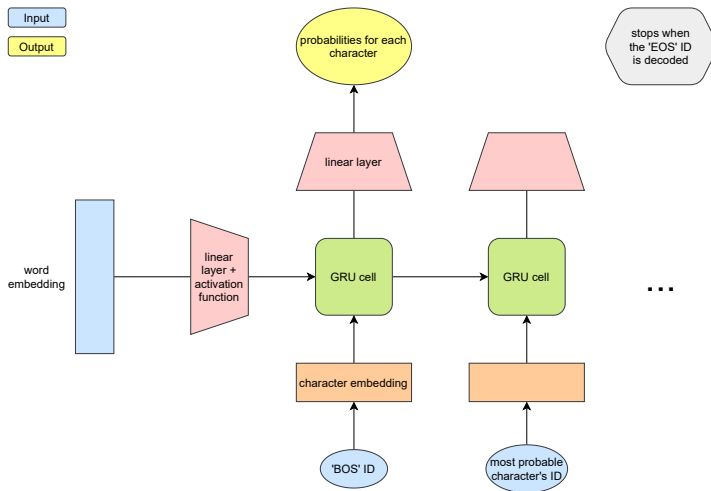
Table: Accuracy (in %) of 10 runs of the omnilingual analogy solving model trained on the full dataset

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	52.41±1.35	24.79±1.89	38.22±2.26	/	48.81±1.33
German	18.40±4.44	31.24±1.25	79.08±1.85	55.48±1.09	/
Hungarian	64.11±2.06	68.52±1.10	10.56±0.37	79.29±1.81	41.26±2.96
Spanish	/	51.27±1.50	80.04±1.64	28.91±0.65	74.57±5.75
Turkish	59.89±1.54	/	26.52±2.69	83.49±2.41	21.86±1.04

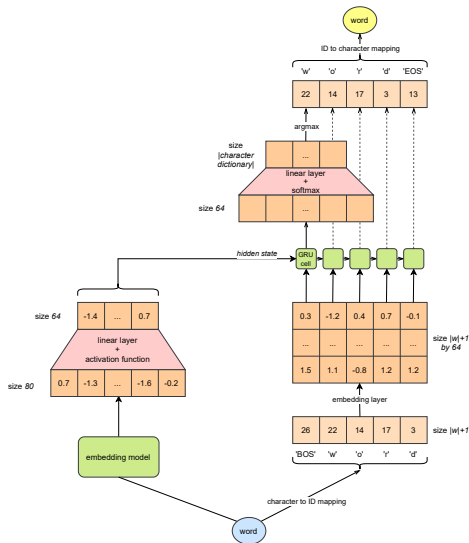
Table: Accuracy (in %) of 10 runs of the omnilingual analogy solver model trained on shared features only

- 1 Omnilingual model
- 2 Decoder**
- 3 Bilingual models

Decoder model: use



Decoder model: training



- 1 Omnilingual model
- 2 Decoder
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Bilingual results

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	/	66.01±33.01	36.28±0.76	/	28.34±0.48
German	64.43±32.23	/	30.53±0.57	11.92±3.30	/
Hungarian	50.61±2.26	77.98±1.24	/	94.02±0.29	33.89±0.77
Spanish	/	32.42±17.01	78.99±0.13	/	40.45±1.52
Turkish	46.43±1.24	/	16.07±0.90	70.86±0.04	/

Table: Accuracy (in %) of 5 runs of the bilingual analogy solver models (diff. parameters)

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	/	83.24±0.35	35.58±0.74	/	28.14±1.14
German	80.13±0.57	/	30.14±0.29	12.92±6.03	/
Hungarian	51.21±3.09	78.09±0.74	/	94.05±0.12	34.55±0.60
Spanish	/	36.79±11.74	79.11±0.63	/	41.83±0.85
Turkish	47.23±0.91	/	15.29±0.85	70.79±0.06	/

Table: Accuracy (in %) of 5 runs of the bilingual analogy solver models (shared parameters)

Monolingual VS Bilingual (different parameters)

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	/	39.75±2.67	80.33±1.95	/	79.89±2.43
German	94.26±0.63	/	70.55±2.61	70.55±2.61	/
Hungarian	43.93±3.44	85.39±1.76	/	85.39±1.76	40.98±3.42
Spanish	/	94.26±0.53	94.26±0.53	/	95.83±0.24
Turkish	64.98±2.76	/	70.74±2.23	94.03±3.70	/

Table: Accuracy (in %) of 10 runs of the monolingual analogy solver models

	Finnish	German	Hungarian	Spanish	Turkish
Finnish	/	66.01±33.01	36.28±0.76	/	28.34±0.48
German	64.43±32.23	/	30.53±0.57	11.92±3.30	/
Hungarian	50.61±2.26	77.98±1.24	/	94.02±0.29	33.89±0.77
Spanish	/	32.42±17.01	78.99±0.13	/	40.45±1.52
Turkish	46.43±1.24	/	16.07±0.90	70.86±0.04	/

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