A Neural Approach for Detecting Morphological Analogies

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Proportional Analogy

Notation:

- $A : B :: C : D$ (read "A is to B as C is to D")

3 Core properties:

1. $A : B :: C : D \longrightarrow C : D :: A : B$ (symmetry)
2. $A : B :: C : D \longrightarrow A : C :: B : D$ (central permutation)
3. $A : B :: A : B$ (reflexively)

Morphology:

- "*read* is to *readable* as *count* is to *countable*"
- *aalto* : *aalloksi* :: *spirituaali* : *spirituaaliksi* (Finnish)

Training and Evaluation Procedure

Analogies obtained by aligning morphological transformations:

- *dog*, to `NUM=PLURAL`, *dogs*
- *cat*, to `NUM=PLURAL`, *cats*
- resulting analogy: *dog* : *dogs* :: *cat* : *cats*

For each analogy $A : B :: C : D$ extracted from the data (use max 50000 of the available analogies):

1. embed A, B, C, and D
2. permute embeddings using properties of proportional analogy:
   - Train. & eval.: 8 valid analogies
   - Training: 3 invalid analogies
   - Evaluation: 3×8 invalid analogies and their equivalent forms
3. aggregate over all permutations:
   - Training: loss (Binary Cross-Entropy)
   - Evaluation: accuracy

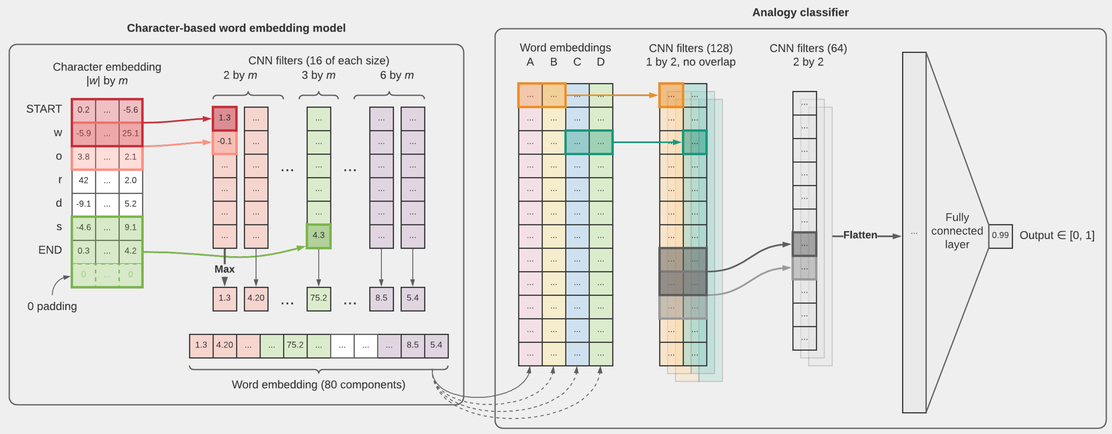
$A : B :: C : D$ (base form)		$C : D :: A : B$
$A : C :: B : D$	$B : A :: D : C$	$D : B :: C : A$
$D : C :: B : A$	$C : A :: D : B$	$B : D :: A : C$

Table: 8 equivalent forms per analogy

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

Table: 3 invalid analogies per analogy

Proposed Approach: Morphological Embedding + CNN Classifier



Classification Results

Language	CNN (ours) Valid	CNN (ours) Invalid	Best Baseline Valid		Best Baseline Invalid		Number of analogies in the data Training	Number of analogies in the data Test
Sigmorphon2016 task 1 (inflexion) [2]								
Arabic	**99.89**	**97.52**	34.21	(Alea@10)	**97.79**	(Kolmo@1)	373240	555312
Finnish	**99.44**	82.62	25.60	(Lepage)	**98.78***	(Alea@1)	1342639	4691453
Georgian	**99.83**	91.71	93.20	(Kolmo@10)	**95.21**	(Alea@1)	3553763	8368323
German	**99.48**	89.01	86.90	(Alea@10)	**97.19**	(Alea@1)	994740	1480256
Hungarian	**99.99**	**98.81**	36.80	(Kolmo@10)	**98.40**	(Kolmo@1)	3280891	66195
Maltese	**99.96**	**77.83**	78.05	(Alea@10)	69.29	(Kolmo@1)	104883	3707
Navajo	**99.53**	90.82	21.45	(Kolmo@10)	**94.93**	(Kolmo@1)	502637	4843
Russian	**97.95**	79.85	42.37	(Alea@10)	**93.88**	(Lepage)	1965533	6421514
Spanish	**99.94**	78.33	85.90	(Alea@10)	**86.62**	(Lepage)	1425838	4794504
Turkish	**99.48**	**92.63**	44.76	(Alea@10)	91.40	(Kolmo@1)	606873	11360
Japanese Bigger Analogy Test Set [4]								
Japanese	**99.99**	**98.65**	19.20	(Kolmo@10)	**98.13**	(Lepage)	18487	7923

123 no significant difference

123 best result, significant difference between baselines and ours

* obtained on 4000 analogies (too slow on 50000)

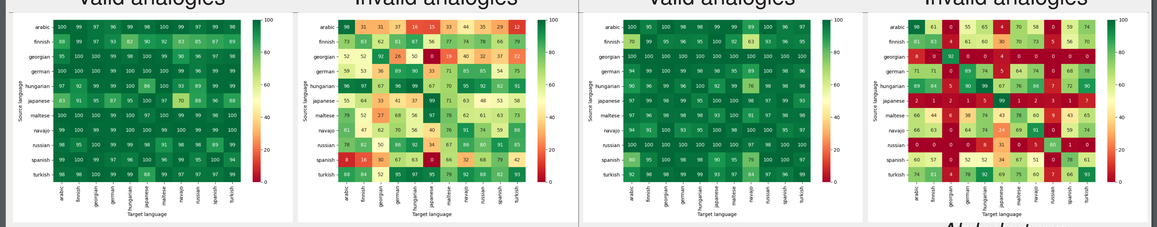
Transferability

Partial transfer (emb. of target clf. of source)

Valid analogies | Invalid analogies

Full transfer (emb. & clf. of source)

Valid analogies | Invalid analogies



Alphabet gap

Baselines

1 Classifier:

- Lepage Classifier [3]
  - matrix based approach to align characters between words and find common sub-words

2 Solvers:

- find missing x making $A : B :: C : x$ valid; if expected D in top 1 or 10 solutions, valid analogy
- Kolmogorov Complexity [6]:
  - minimize complexity of f such that $B = f(A)$ and $f(C)$ is computable; $x = f(C)$
- Alea [5]:
  - random permutations of the characters of B not in A and those of C (Monte-Carlo method)

Perspectives

- ✓ explore transferability [1]
- ✓ balancing data
- ✓ regression (analogy solving)
- qualitative analysis of embedding model
- other domains (images, text, explanations, *etc.*)

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