Predicting grammatical gender in Nakh languages Three methods compared

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24/08/2022

55th Annual Meeting of the Societas Linguistica Europaea University of Bucharest "lorgu lordan – Al. Rosetti" Institute of Linguistics

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- Some systems where assignment is completely transparent, others where it is more opaque

Our approach

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- Three computational methods to test which factors most adequately predict gender in Chechen and Tsova-Tush

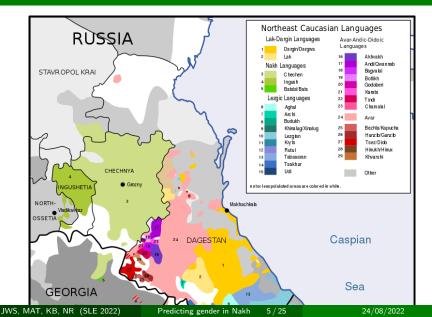
Studies concerning gender prediction

- Network Morphology approach (Corbett and Fraser (1993)) with a lexical knowledge representation language (DATR) (Fraser & Corbett, 1995; Evans & Gazdar, 1989a, 1989b, 1996)
- Polinsky and van Everbroeck (2003): study of the reanalysis of the Latin gender system as it transitioned to Old French, with frequency-based neural network
- Bateman and Polinsky (2010): decision trees to reconsider the gender system of Romanian as a two-value rather than the traditional three-value analysis
- Plaster, Polinsky and Harizanov (2012): decision tree model that predicts gender of 70% of nouns in Tsez (East-Caucasian. Result: semantic features are the most predictive
- Allassonnière-Tang, Brown and Fedden (2021): simple decision trees + random forest trees + neural networks to test claim that Mian (Ok) assigns gender predominantly on basis of semantics.

JWS, MAT, KB, NR (SLE 2022)

Background

Nakh languages



Chechen and Tsova-Tush

Chechen	Tsova-Tush
	• aka Bats, aka Batsbi
 Chechnya (RF) 	 Georgia>Zemo Alvani
 95% of Chechnya 	• 500 people
 Official 	 Not official
 Bilingualism with Russian 	• Bilingualism with Georgian
 Not endangered 	 Severely endangered
	<u>I</u>

Background





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 Agreement with head noun
 the numeral 'four'

(1) Chechen (Nichols, 1994: 37)

 $c\hbar a \ jiett \ \bar{a}ra \ b-\bar{e}l-ir.$ one cow(B) out B-go-AOR

'One cow went out.'

(2) Tsova-Tush (Kadagidze, 2009: 170)

se herc'ŏ d-ux d-erc'-d-Ø-eb so ! 1SG.GEN pot(D) D-back D-return-D-TR-IMP 1SG.DAT 'Give me back my pot!'

Gender	Semantics	Markers (SG/PL)		
		Tsova-Tush	Chechen	
М	male rationals	v- / b-	v- / b-	
F	female rationals	j- / d-	j- / b-	
В	animals, inanimates	b- / d-	b- / d-	
J	animals, inanimates	j- / j-	j- / j-	
D	animals, inanimates	d- / d-	d- / d-	
Bb	animals, inanimates	b- / b- (6 items)	b- / b- (22 items)	
Bj	body parts, 'step', 'kick'	b- / j- (17 items)	-	
Dj	body parts	d- / j- (6 items)	-	

Last 3 = exceptions aka 'inquorate' genders, (Corbett, 1991: 170–175), excluded from this study

Background

Gender assignment in Chechen and Tsova-Tush

- M & F = male vs. female rationals
- vs. 3 non-fully predictable non-rational genders



Gender assignment in Chechen and Tsova-Tush

Table: Tendencies which predict gender of small portion of non-rationals

Chechen (Nichols 2007)	Tsova-Tush (Wichers Schreur 2021)
	Some semantically-based clusterings of genders \rightarrow 15% of non-rationals predicted
Some derived abstract nouns \rightarrow D/J depending on degree of abstractness	All verbal nouns \rightarrow D class Most de-adjectival abstract nouns \rightarrow J class
	60-65% of b-, d- and j- nouns \rightarrow B, D and J genders (auto- gender + alliterative concord)

Background

Gender assignment in Chechen and Tsova-Tush

Table: Special cases

	Chechen	Tsova-Tush
Loanwords	New loanwords often	Same set of semantic and
	given gender of near	phonological tendencies
	synonym or immediate	as native nouns (Wichers
	generic (Nichols 2007),	Schreur 2021)
	but all recent Russian	
	loans have gender J	

Two lexical databases

- Chechen: Erwin Komen combined dictionaries of Matsiev (1961) and Jamalkhanov and Aliroev (1991)
- Tsova-Tush: Kadagidze and Kadagidze (1984)

Language	В	D	J	М	F
Chechen	320	868	1370	88	27
Tsova-Tush	462	968	836	104	30

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- Form information: the first three and the last three phonemes of each noun (Dryer, 2013; Basirat et al., 2021)

Language	В	D	J	Μ	F
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Noun	haer	mar
Gloss	air	husband
Gender	J	Μ
Concepticon_category	Person/thing	Person/thing
Concepticon_field	Physical world	Kinship
Semantic_broad	Inanimate	Male
Semantic_domain	Natural	Kinship
Borrowed_Arab	0	0
Borrowed_GE	1	0
Borrowed_Turk	0	0
Borrowed_Russian	0	0
Word length	4	3
Last first phoneme	r	r
Last second phoneme	е	а
Last third phoneme	а	m
First phoneme	h	m
Second phoneme	а	а
Third phoneme	e	r
		24/00/2

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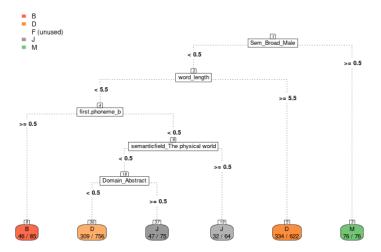
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- The performance is compared with the random baseline (38.4%, 30.5%) and the majority baseline (51.3%, 39.2%)
- The use of precision and recall to assess the performance on each gender category (like Target-Like Usage (TLU) and Suppliance in Obligatory Context (SOC) in language acquisition)

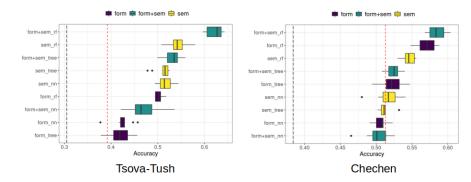
Output



Example tree for gender assignment in Tsova-Tush

Data and methods

Output



Overall prediction accuracy across the languages of the study. The dashed lines indicate the random (black) and the majority (red) baselines.

Tsova-Tush:

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 - "Inanimate" \rightarrow gender J (51% accuracy)

Chechen:

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- New findings:
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 - Russian loanwords \rightarrow J gender (55/69 neuter words) (not mirrored in decision tree experiments).

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- However, more data is always needed... (lexicon and semantic features)



Thank you! 24/08/2022 JWS, MAT, KB, NR (SLE 2022) Predicting gender in Nakh

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