The Illiterati

Part-of-speech tagging for Magahi and Bhojpuri without even knowing the alphabet

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NLP Solutions for Under Resourced Languages (NSURL 2019)

Tasks 9 and 10: Part-of-speech tagging for Magahi and Bhojpuri

	Magahi	Bhojpuri
tag set	18	33
training	61.435	94.692
test	8.205	10.582

Our strategies

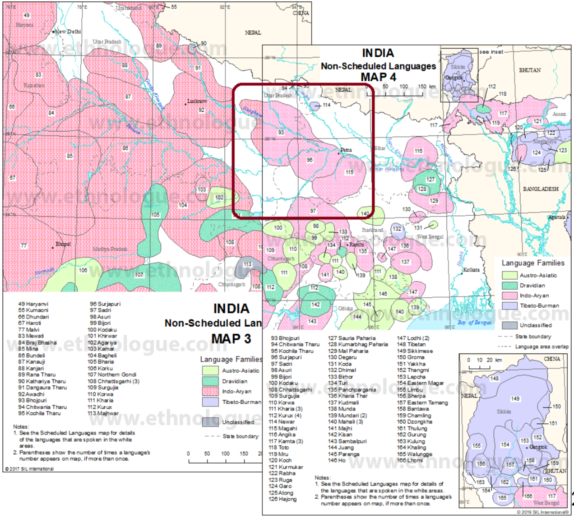
- use customisable off-the-shelf taggers
- include additional resources (transfer learning)
  - Brown clusters
  - word embeddings
  - tagged corpora of related languages

Language Map: Bhojpuri in India

 [1]

[1] source:https://commons.wikimedia.org/wiki/File:Bhojpuri_Speaking_Region_in_India.png

Language Map: Magahi and Bhojpuri



[2]

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[2] sources: https://www.ethnologue.com/map/IN_03, https://www.ethnologue.com/map/IN_04

About Magahi and Bhojpuri

- principal languages of the Bihari group (West-Eastern Indo-Aryan language)
  - Magahi
  - Bhojpuri
  - Maithili
- Bhojpuri: approx. 51 million native speakers (2011 census), spoken in Western Bihar, Eastern Uttar Pradesh, and in Southwest Nepal
- Magahi: approx. 13 million native speakers (21 million if Khortha, a prominent dialect, is also included), mainly spoken in Southern Bihar

Interesting features w.r.t. POS tagging

- SOV order
- rich verb morphology
- extensive use of postpositions
- Magahi: unusual agreement system (verb has to agree with subject *and* object)

Three off-the-shelf POS Taggers

- SoMeWeTa[3] (Proisl, 2018)
  - based on averaged structured perceptron
  - supports domain adaptation and external resources
- BiLSTM+CRF sequence tagger (Guillaume Genthial, Riedl and Padó (2018)[4])
  - based on character and word embeddings
  - supports transfer learning
- The Stanford Tagger[5] (Toutanova et al., 2003)
  - based on a maximum entropy cyclic dependency network
  - hyperparameter tuning

[3] https://github.com/tsproisl/SoMeWeTa
[4] https://github.com/riedlma/sequence_tagging
[5] https://nlp.stanford.edu/software/tagger.html

Additional Resources

freely available resources used in addition to training data

- Hindi UD treebank (HDTB; ca. 352,000 tokens)[6]
- Two Magahi corpora[7]
  - POS-tagged Magahi corpus (KMI-Mag; ca. 46,000 tokens)
  - Corpus of untagged Magahi texts (ca. 2.8 million tokens)
- Plain text extracted from Wikimedia dumps[8]
  - Hindi (ca. 34.7 million tokens)
  - Bihari (ca. 700,000 tokens)
- Brown clusters (Brown et al., 1992) computed from Wikimedia dumps and untagged Magahi corpus
- Pre-trained fastText embeddings for Hindi and Bihari[9]

[6] https://github.com/UniversalDependencies/UD_Hindi-HDTB
[7] https://github.com/kmi-linguistics/magahi
[8] https://dumps.wikimedia.org
[9] https://fasttext.cc/docs/en/crawl-vectors.html

Experiments Using SoMeWeTa

Focus on Brown clusters and transfer learning

Cross-validation results on training data (selection)

model	accuracy
Bhojpuri (no additional resources)	91.62 (±0.97)
Bhojpuri (hi)	91.79 (±1.00)
Bhojpuri (hi+mag)	91.99 (±0.83)
Bhojpuri (hi+bh+mag)	92.04 (±0.80)
KMI-Mag → Bhojpuri (hi+bh+mag)	*92.06 (±0.94)*
Magahi (no additional resources)	88.92 (±1.24)
Magahi (mag)	89.12 (±1.23)
Magahi (hi+mag)	*89.32 (±1.15)*
Magahi (hi+bh+mag)	89.15 (±1.17)
KMI-Mag+Bhojpuri → Magahi (hi+mag)	89.30 (±1.14)

Brown clusters beneficial, additional transfer learning not

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Magahi (hi+bh+mag)	89.15 ($\pm$1.17)
KMI-Mag+Bhojpuri $\rightarrow$ Magahi (hi+mag)	89.30 ($\pm$1.14)

Brown clusters beneficial, additional transfer learning not

Experiments Using the BiLSTM-CRF Tagger

Focus on embeddings and transfer learning

Cross-validation results on training data

model	accuracy
Magahi (Hindi embeddings)	88.97 ($\pm$1.14)
Magahi (Bihari embeddings)	89.09 ($\pm$1.00)
HDTB $\rightarrow$ Magahi (Hindi embeddings)	89.85 ($\pm$0.99)
KMI-Mag $\rightarrow$ Magahi (Hindi embeddings)	*90.70 ($\pm$0.92)*
Bhojpuri (Hindi embeddings)	90.78 ($\pm$0.55)
Bhojpuri (Bihari embeddings)	90.80 ($\pm$0.57)
KMI-Mag $\rightarrow$ Bhojpuri (Hindi embeddings)	*91.23 ($\pm$0.68)*

Using Hindi embeddings and pretraining on KMI-Mag works best for both languages!

Experiments Using the BiLSTM-CRF Tagger

Focus on embeddings and transfer learning

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model	accuracy
Magahi (Hindi embeddings)	88.97 ($\pm$1.14)
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KMI-Mag $\rightarrow$ Bhojpuri (Hindi embeddings)	*91.23 ($\pm$0.68)*

Using Hindi embeddings and pretraining on KMI-Mag works best for both languages!

Experiments Using the Stanford Tagger: Magahi

parameter	default	value/range
closedClassTags	(none)	ADP AUX CCONJ DET NUM PART PRON SCONJ PUNCT
arch/macro	generic	generic, left3word, bidirectional5words
arch/further unknown-words option	(none)	naacl2003unknowns
arch/unicode shapes for rare words	(none)	(-2,2), (-1,1), (0), (none)
iterations	100	100
learnClosedClassTags	false	false
curWordMinFeatureThresh	2	1..4
minFeatureThresh	5	1..5
rareWordMinFeatureThresh	10	1..10
rareWordThresh	5	1..8
veryCommonWordThresh	250	100, 150, 200, 250

- 76,800 hyperparameter combinations
- 2 runs per parameter combination (first and last 20% as test data)

153,600 training cycles (FAU HPC)

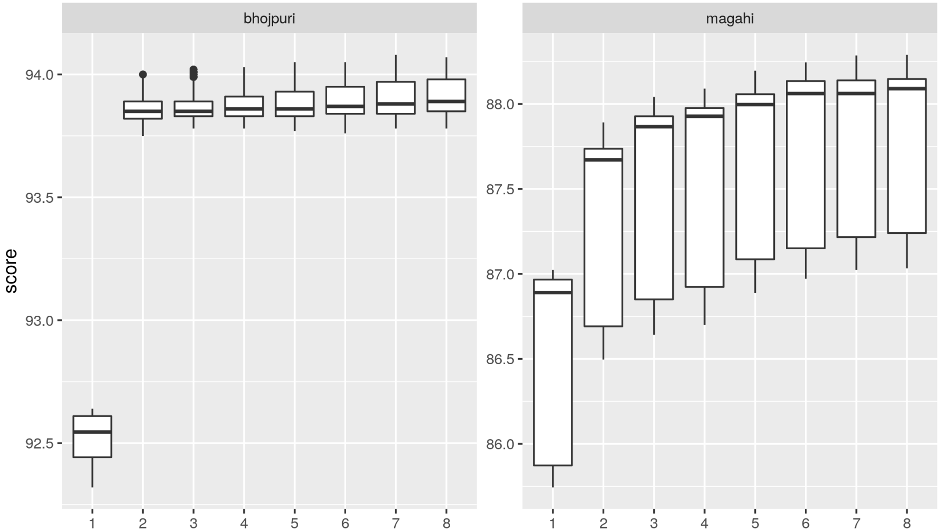
Experiments Using the Stanford Tagger: Bhojpuri

parameter	default	value/range
closedClassTags	(none)	(none)
arch/macro	generic	generic, left3word, bidirectional5words
arch/further unknown-words option	(none)	naacl2003unknowns
arch/unicode shapes for rare words	(none)	(-2,2), (-1,1), (0), (none)
iterations	100	100
learnClosedClassTags	false	true
closedClassTagThreshold	40	40
curWordMinFeatureThresh	2	1..4
minFeatureThresh	5	1..5
rareWordMinFeatureThresh	10	1..10
rareWordThresh	5	1..8
veryCommonWordThresh	250	100, 150, 200, 250

- 76,800 parameter combinations
- full 10-fold crossvalidation

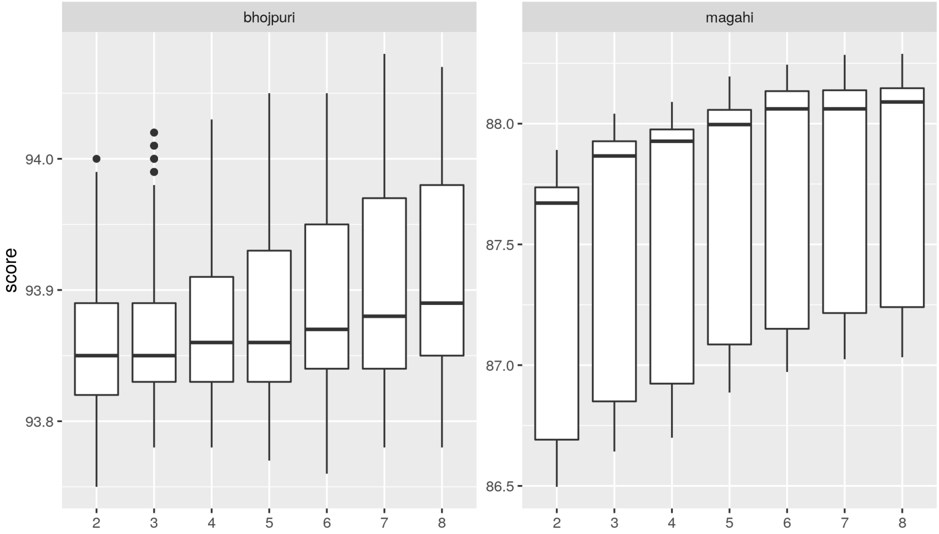
768,000 training cycles (FAU HPC)

Parameter Analysis: rareWordThresh



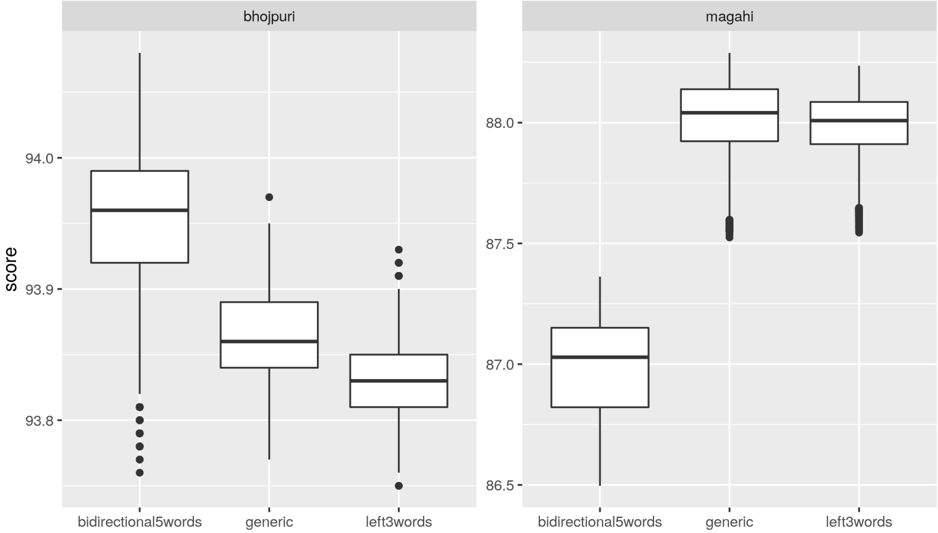
Parameter Analysis: rareWordThresh

exluding rareWordThresh=1



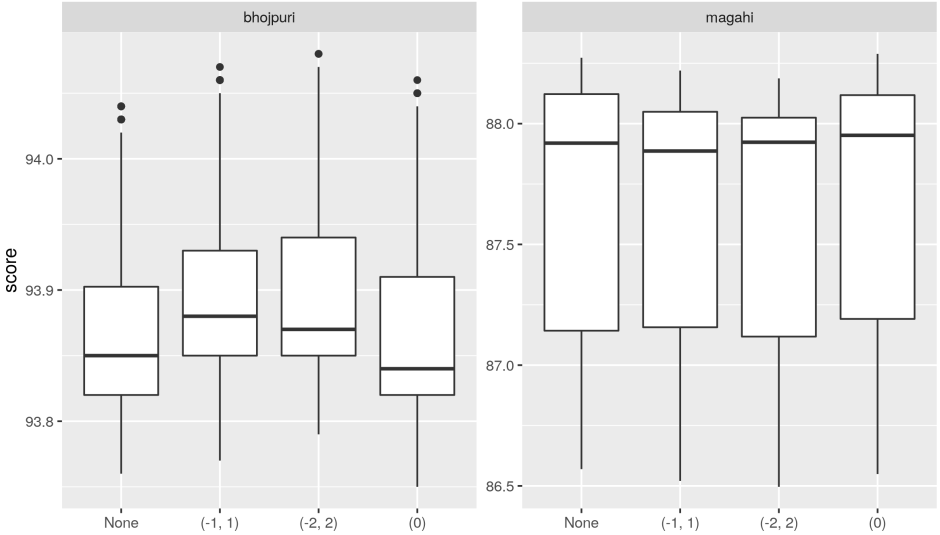
Parameter Analysis: macro

exluding rareWordThresh=1



Parameter Analysis: unicodeshape

exluding rareWordThresh=1



Parameter Analysis: Summary

- performance decreases abruptly when *rareWordThresh* is set to 1 (at least hapax legomena should be treated as rare words)
- performance was insensitive to variation in *veryCommonWordThresh* (this option was ignored by the system)
- macro has most influence
  - Bhojpuri: `bidirectional5words`
  - Magahi: `generic` and `left3words` training data annotation?
- *rareWordThresh* explains most of the remaining variation

Official Results

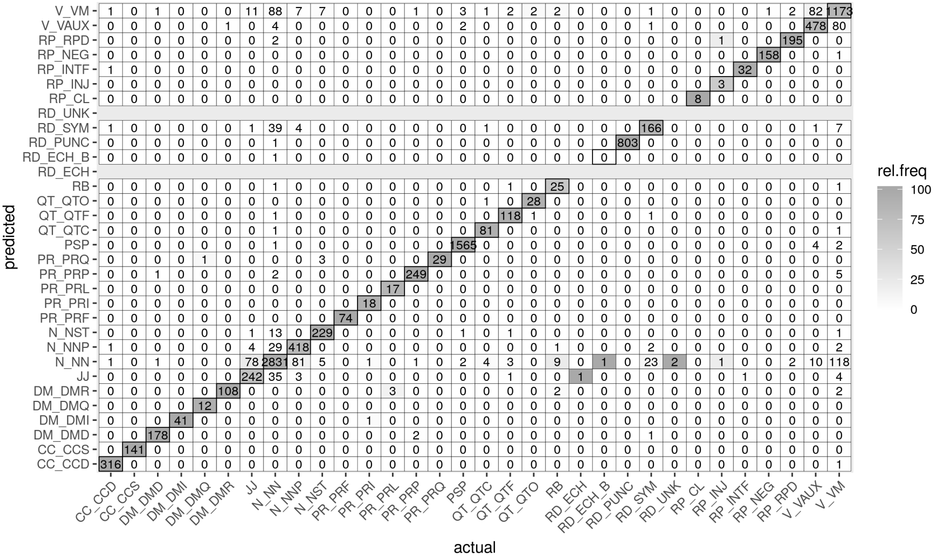
	submission	F_1	acc.
1	**Stanford**	95	94.78
1	NITK-NLP_SUB1	95	
2	**SoMeWeTa**	93	92.76
3	**BiLSTM-CRF**	92	92.01
4	NITK-NLP_SUB2	89	

Table: Results for Bhojpuri

	submission	F_1	acc.
1	NITK-NLP_SUB2	79	
2	**BiLSTM-CRF**	77	78.86
2	**SoMeWeTa**	77	78.68
3	**Stanford**	74	76.57
4	NITK-NLP_SUB1	73	

Table: Results for Magahi

Bhojpuri: Confusion Matrix for BiLSTM

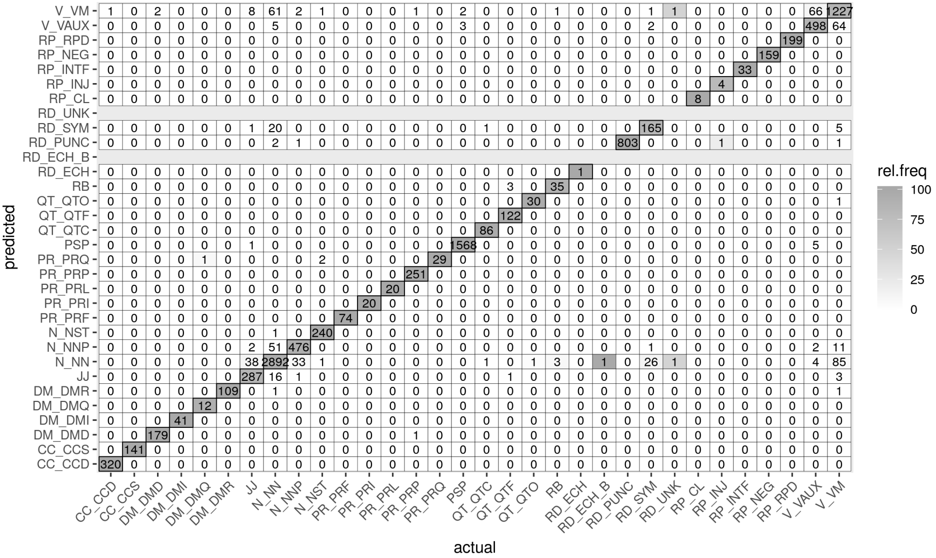


Bhojpuri: Confusion Matrix for SoMeWeTa

predicted \ actual	CC_CCD	CC_CCS	DM_DMD	DM_DMI	DM_DMQ	DM_DMR	JJ	N_NN	N_NNP	N_NST	PR_PRF	PR_PRI	PR_PRL	PR_PRP	PR_PRQ	PSP	QT_QTC	QT_QTF	QT_QTO	RB	RD_ECH	RD_ECH_B	RD_PUNC	RD_SYM	RD_UNK	RP_CL	RP_INJ	RP_INTF	RP_NEG	RP_RPD	V_VAUX	V_VM
V_VM	1	0	1	0	0	0	7	86	1	4	0	1	0	3	0	2	0	2	0	0	0	0	0	2	1	0	0	0	0	4	80	1179
V_VAUX	0	0	0	0	0	1	0	6	0	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	481	66
RP_RPD	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	195	0	0
RP_NEG	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	159	0	0	1
RP_INTF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	0	0	0	1
RP_INJ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0
RP_CL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0
RD_UNK																																
RD_SYM	0	0	0	0	0	0	1	29	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	158	0	0	0	0	0	0	0	5
RD_PUNC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	803	2	0	0	0	0	0	0	1	0
RD_ECH_B																																
RD_ECH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
RB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	30	0	0	0	0	0	0	0	0	0	0	0	0
QT_QTO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	1
QT_QTF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	117	1	0	0	0	0	0	0	0	0	0	0	0	0	0
QT_QTC	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	84	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
PSP	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1567	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	3
PR_PRQ	0	0	0	0	0	0	0	0	0	2	0	1	0	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PR_PRP	0	0	1	0	0	0	0	1	0	0	0	0	0	249	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3
PR_PRL	0	0	0	0	0	0	0	1	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PR_PRI	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PR_PRF	0	0	0	0	0	0	0	0	1	0	74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
N_NST	0	0	0	0	1	0	1	5	0	232	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
N_NNP	0	0	0	0	0	0	3	43	449	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	8
N_NN	1	0	1	0	0	0	74	2851	57	5	0	3	0	0	0	0	3	3	1	6	0	1	0	32	1	0	1	0	0	0	6	115
JJ	0	0	0	0	0	0	250	24	4	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	10
DM_DMR	0	0	0	0	0	108	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	3
DM_DMQ	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DM_DMI	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DM_DMD	0	0	178	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CC_CCS	0	141	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CC_CCD	319	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

rel.freq: 100, 75, 50, 25, 0

Bhojpuri: Confusion Matrix for Stanford Tagger



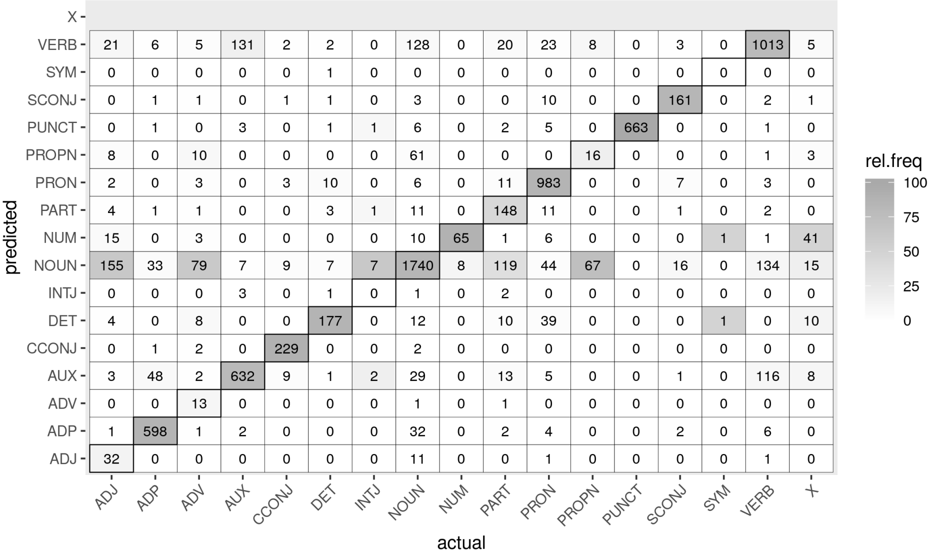
predicted \ actual	CC_CCD	CC_CCS	DM_DMD	DM_DMI	DM_DMQ	DM_DMR	JJ	N_NN	N_NNP	N_NST	PR_PRF	PR_PRI	PR_PRL	PR_PRP	PR_PRQ	PSP	QT_QTC	QT_QTF	QT_QTO	RB	RD_ECH	RD_ECH_B	RD_PUNC	RD_SYM	RD_UNK	RP_CL	RP_INJ	RP_INTF	RP_NEG	RP_RPD	V_VAUX	V_VM
V_VM	1	0	2	0	0	0	8	61	2	1	0	0	0	1	0	2	0	0	0	1	0	0	0	1	1	0	0	0	0	0	66	1227
V_VAUX	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	2	0	0	0	0	0	0	498	64
RP_RPD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	199	0	0
RP_NEG	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	159	0	0	0
RP_INTF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	0	0	0	0
RP_INJ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0
RP_CL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0
RD_UNK																																
RD_SYM	0	0	0	0	0	0	1	20	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	165	0	0	0	0	0	0	0	5
RD_PUNC	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	803	0	0	0	1	0	0	0	0	1
RD_ECH_B																																
RD_ECH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
RB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	35	0	0	0	0	0	0	0	0	0	0	0	0
QT_QTO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	1
QT_QTF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	122	0	0	0	0	0	0	0	0	0	0	0	0	0	0
QT_QTC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	86	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PSP	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1568	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0
PR_PRQ	0	0	0	0	1	0	0	0	0	2	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PR_PRP	0	0	0	0	0	0	0	0	0	0	0	0	0	251	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PR_PRL	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PR_PRI	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PR_PRF	0	0	0	0	0	0	0	0	0	0	74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
N_NST	0	0	0	0	0	0	0	1	0	240	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
N_NNP	0	0	0	0	0	0	2	51	476	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	11
N_NN	0	0	0	0	0	0	38	2892	33	1	0	0	0	0	0	0	1	0	1	3	0	1	0	26	1	0	0	0	0	0	4	85
JJ	0	0	0	0	0	0	287	16	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3
DM_DMR	0	0	0	0	0	109	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
DM_DMQ	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DM_DMI	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DM_DMD	0	0	179	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CC_CCS	0	141	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CC_CCD	320	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Magahi: Confusion Matrix for Stanford Tagger

predicted \ actual	ADJ	ADP	ADV	AUX	CCONJ	DET	INTJ	NOUN	NUM	PART	PRON	PROPN	PUNCT	SCONJ	SYM	VERB	X
X																	
VERB	11	6	4	246	4	2	2	87	1	23	7	2	0	1	0	978	5
SYM																	
SCONJ	0	1	1	0	0	0	0	0	0	0	3	0	0	158	0	0	0
PUNCT	0	0	0	0	0	0	0	0	0	0	0	0	663	0	0	0	0
PROPN	0	0	0	0	0	0	0	6	0	0	0	3	0	0	0	0	6
PRON	1	0	1	0	3	6	0	1	0	5	994	0	0	16	0	1	0
PART	3	0	0	1	0	2	0	1	0	110	5	0	0	0	0	1	0
NUM	7	0	1	0	0	0	0	1	57	0	3	0	0	0	1	0	40
NOUN	188	46	100	216	5	12	3	1929	15	175	84	86	0	14	0	235	22
INTJ	0	0	0	0	0	0	6	1	0	0	0	0	0	0	0	0	0
DET	10	2	12	0	0	182	0	9	0	10	31	0	0	0	1	1	10
CCONJ	0	0	1	0	240	0	0	0	0	0	0	0	0	0	0	0	0
AUX	1	15	0	313	1	0	0	4	0	5	3	0	0	2	0	61	0
ADV	0	0	7	0	0	0	0	1	0	0	1	0	0	0	0	2	0
ADP	1	619	1	2	0	0	0	12	0	1	0	0	0	0	0	1	0
ADJ	23	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0

rel.freq: 100, 75, 50, 25, 0

Magahi: Confusion Matrix for BiLSTM



predicted \ actual	ADJ	ADP	ADV	AUX	CCONJ	DET	INTJ	NOUN	NUM	PART	PRON	PROPN	PUNCT	SCONJ	SYM	VERB	X
X																	
VERB	21	6	5	131	2	2	0	128	0	20	23	8	0	3	0	1013	5
SYM	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
SCONJ	0	1	1	0	1	1	0	3	0	0	10	0	0	161	0	2	1
PUNCT	0	1	0	3	0	1	1	6	0	2	5	0	663	0	0	1	0
PROPN	8	0	10	0	0	0	0	61	0	0	0	16	0	0	0	1	3
PRON	2	0	3	0	3	10	0	6	0	11	983	0	0	7	0	3	0
PART	4	1	1	0	0	3	1	11	0	148	11	0	0	1	0	2	0
NUM	15	0	3	0	0	0	0	10	65	1	6	0	0	0	1	1	41
NOUN	155	33	79	7	9	7	7	1740	8	119	44	67	0	16	0	134	15
INTJ	0	0	0	3	0	1	0	1	0	2	0	0	0	0	0	0	0
DET	4	0	8	0	0	177	0	12	0	10	39	0	0	0	1	0	10
CCONJ	0	1	2	0	229	0	0	2	0	0	0	0	0	0	0	0	0
AUX	3	48	2	632	9	1	2	29	0	13	5	0	0	1	0	116	8
ADV	0	0	13	0	0	0	0	1	0	1	0	0	0	0	0	0	0
ADP	1	598	1	2	0	0	0	32	0	2	4	0	0	2	0	6	0
ADJ	32	0	0	0	0	0	0	11	0	0	1	0	0	0	0	1	0

Magahi: Confusion Matrix for SoMeWeTa

predicted \ actual	ADJ	ADP	ADV	AUX	CCONJ	DET	INTJ	NOUN	NUM	PART	PRON	PROPN	PUNCT	SCONJ	SYM	VERB	X
X	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
VERB	6	4	5	89	5	1	2	153	0	99	7	21	0	2	0	950	5
SYM																	
SCONJ	0	1	2	1	2	1	0	5	0	1	6	0	0	159	0	0	0
PUNCT	0	0	0	0	0	0	0	0	0	0	0	0	663	0	0	0	0
PROPN	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0
PRON	2	0	3	3	5	8	0	6	0	10	1010	0	0	10	0	5	0
PART	9	0	1	1	0	2	0	5	0	107	6	0	0	0	0	2	0
NUM	22	0	0	1	0	0	0	10	69	1	5	2	0	1	1	2	41
NOUN	158	31	79	96	5	7	6	1802	4	79	47	66	0	9	0	175	15
INTJ	0	0	0	0	0	0	3	0	0	0	0	0	0	1	0	0	0
DET	8	1	14	0	0	180	0	15	0	12	40	1	0	0	1	2	10
CCONJ	0	0	2	0	235	1	0	3	0	0	1	1	0	3	0	0	0
AUX	1	13	1	581	1	1	0	14	0	13	4	0	0	2	0	136	12
ADV	0	0	19	0	0	0	0	4	0	1	3	0	0	0	0	0	0
ADP	1	639	1	6	0	0	0	28	0	4	2	0	0	4	0	1	0
ADJ	38	0	1	0	0	3	0	7	0	1	0	0	0	0	0	6	0

rel.freq: 100, 75, 50, 25, 0

Error Analysis: Summary

- Bhojpuri ($F_1 \in [89, 95]$)
  - errors very much what one would expect
  - rare categories show low recall
  - frequent tags (N_NN, V_VM) go-to labels for misclassifications
  - confusion of similar morphosyntactic categories (V_VM $\leftrightarrow$ V_AUX, N_NN $\leftrightarrow$ N_NNP)
- Magahi ($F_1 \in [73, 79]$)
  - major problems:
    - recall for PROPN, X
    - ADJ (15.5%), ADV (14.8%), PART (32.5%)
  - go-to labels NOUN and VERB
  - obvious confusion: VERB $\leftrightarrow$ AUX
  - different tag distributions in test and training data
    - 602 ADJ and 16777 NOUN in the training set
    - 245 ADJ and 2053 NOUN in the test set

Conclusion

- results for Bhojpuri very satisfying
  - close to 95% accuracy on a tagset (33 tags, 100,000 tokens training data)
  - a bit of a downer: mindless parameter-tuning yields best results
  - differences in system performance probably not significant
- results for Magahi very disappointing
  - problems with a-priori tag distribution
  - here: use of additional resources outperforms mere parameter-tuning

Thanks for listening.

Questions?

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