Language technology for low-resource languages

Day 5/5

LOT 2018, Groningen

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Cross-lingual tagging with character embeddings

- Use related languages
- Adapt the HRL tagger to LRL by including a small number of annotated LRL sentences
- Full morphological tagging

R. Cotterell & G. Heigold (2017): *Cross-lingual Character-Level Neural Morphological Tagging*. Proceedings of EMNLP.

Cross-lingual tagging with character embeddings

Romance				Slavic			
lang	train	dev	test	lang	train	dev	test
(ca)	13123	1709	1846	(bg)	8907	1115	1116
(es)	14187	1552	274	(cs)	61677	9270	10148
(fr)	14554	1596	298	(pl)	6800	7000	727
(it)	12837	489	489	(ru)	4029	502	499
(pt)	8800	271	288	(sk)	8483	1060	1061
(ro)	7141	1191	1191	(uk)	200	30	25
Germanic				**Uralic**			
lang	train	dev	test	lang	train	dev	test
(da)	4868	322	322	(et)	14510	1793	1806
(no)	15696	2410	1939	(fi)	12217	716	648
(sv)	4303	504	1219	(hu)	1433	179	188

Table 2: Number of tokens in each of the train, development and test splits (organized by language family).

Cross-lingual tagging with character embeddings

- Results for Romance languages (100 LRL training sentences):

source language		(ca)	(es)	(fr)	(it)	(pt)	(ro)
	(ca)	—	87.9%	84.2%	84.6%	81.1%	67.4%
	(es)	88.9%	—	85.5%	85.6%	81.8%	69.5%
	(fr)	88.3%	87.0%	—	83.6%	79.5%	**69.9%**
	(it)	88.4%	87.8%	84.2%	—	80.6%	69.1%
	(pt)	88.4%	88.9%	85.1%	84.7%	—	69.6%
	(ro)	87.6%	87.2%	85.0%	84.4%	79.9%	—

Cross-lingual tagging with character embeddings

- Results for Slavic languages (100 LRL training sentences):

source language	(bg)	(cs)	(pl)	(ru)	(sk)	(uk)
(bg)	—	47.4%	44.7%	67.3%	39.7%	57.3%
(cs)	57.8%	—	56.5%	62.6%	62.6%	54.0%
(pl)	54.3%	54.0%	—	59.3%	57.8%	48.0%
(ru)	**68.8%**	48.6%	47.4%	—	46.5%	**60.7%**
(sk)	55.2%	57.4%	54.8%	61.2%	—	49.3%
(uk)	44.1%	36.0%	34.4%	43.2%	30.0%	—

Cross-lingual tagging with character embeddings

- Results for Northern Germanic languages:

		(da)	(no)	(sv)
source	(da)	—	77.6%	73.1%
	(no)	83.1%	—	75.7%
	(sv)	81.4%	76.5%	—

- Results for Uralic languages:

		(et)	(fi)	(hu)
source	(et)	—	60.9%	60.4%
	(fi)	60.1%	—	60.3%
	(hu)	47.1%	48.3%	—

Cross-lingual tagging with character embeddings

- No parallel data, no dictionary mappings, but small annotated LRL training set
  - Model adaptation approach
- Some missing baselines:
  - Train on only 100 LRL sentences, without HRL data
  - Train only on HRL data without LRL sentences
- In the absence of these comparisons, results look rather low for most languages
- Cross-lingual character embedding mappings?

Why not use all source languages?

source language	(ca)	(es)	(fr)	(it)	(pt)	(ro)
(ca)	—	87.9%	84.2%	84.6%	81.1%	67.4%
(es)	88.9%	—	85.5%	85.6%	81.8%	69.5%
(fr)	88.3%	87.0%	—	83.6%	79.5%	**69.9%**
(it)	88.4%	87.8%	84.2%	—	80.6%	69.1%
(pt)	88.4%	88.9%	85.1%	84.7%	—	69.6%
(ro)	87.6%	87.2%	85.0%	84.4%	79.9%	—
multi-source	**89.8%**	**90.9%**	**86.6%**	**86.8%**	**83.4%**	67.5%

Why not use all source languages?

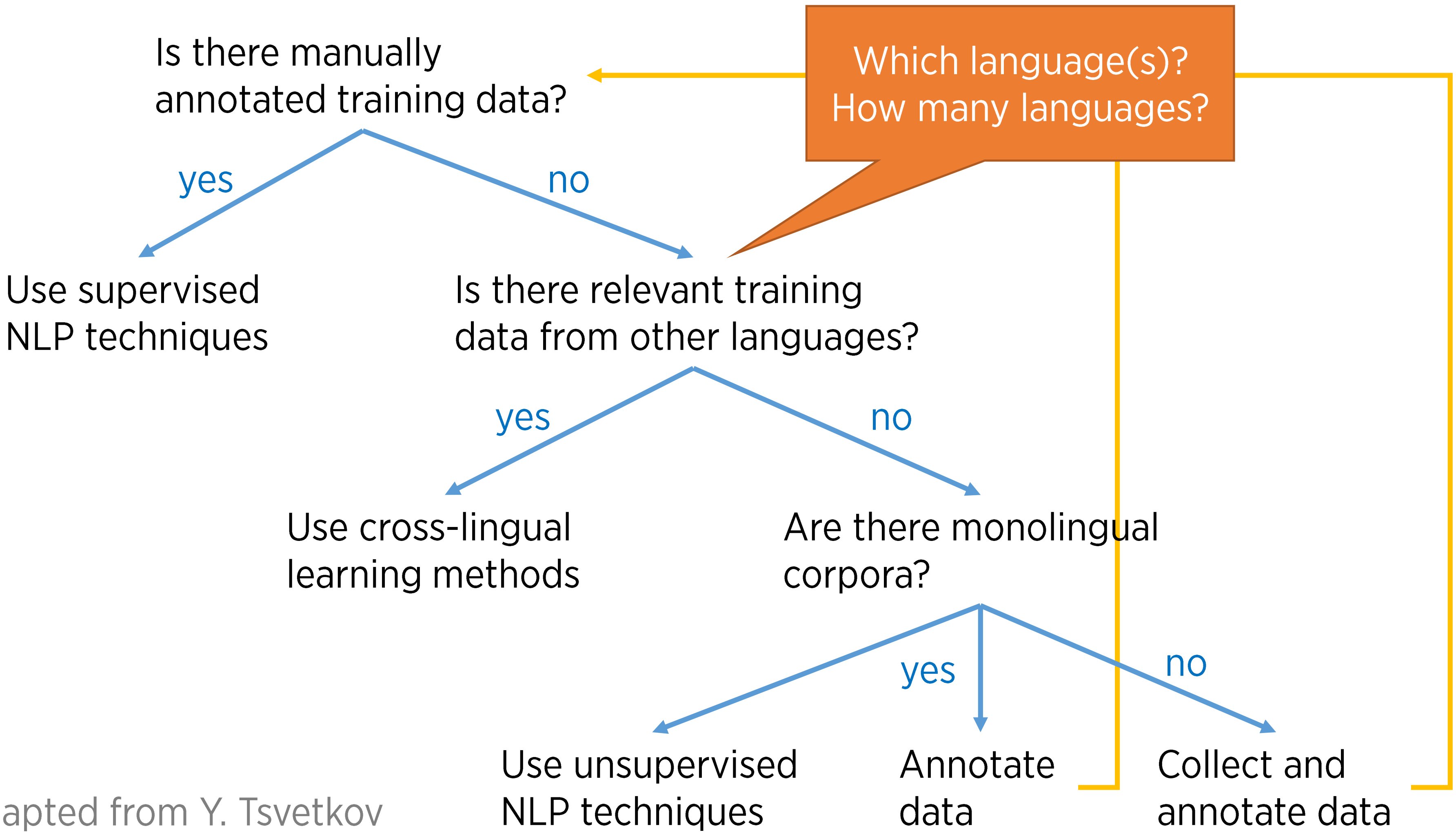
source language		(bg)	(cs)	(pl)	(ru)	(sk)	(uk)
	(bg)	—	47.4%	44.7%	67.3%	39.7%	57.3%
	(cs)	57.8%	—	56.5%	62.6%	62.6%	54.0%
	(pl)	54.3%	54.0%	—	59.3%	57.8%	48.0%
	(ru)	**68.8%**	48.6%	47.4%	—	46.5%	**60.7%**
	(sk)	55.2%	57.4%	54.8%	61.2%	—	49.3%
	(uk)	44.1%	36.0%	34.4%	43.2%	30.0%	—
	multi-source	64.5%	**57.9%**	**57.0%**	**64.4%**	**64.8%**	58.7%

Why not use all source languages?

		(da)	(no)	(sv)
source	(da)	—	77.6%	73.1%
	(no)	83.1%	—	75.7%
	(sv)	81.4%	76.5%	—
	multi-source	**87.8%**	**82.3%**	**77.2%**

		(et)	(fi)	(hu)
source	(et)	—	**60.9%**	**60.4%**
	(fi)	**60.1%**	—	60.3%
	(hu)	47.1%	48.3%	—
	multi-source	54.7%	55.3%	55.4%

Multilingual models



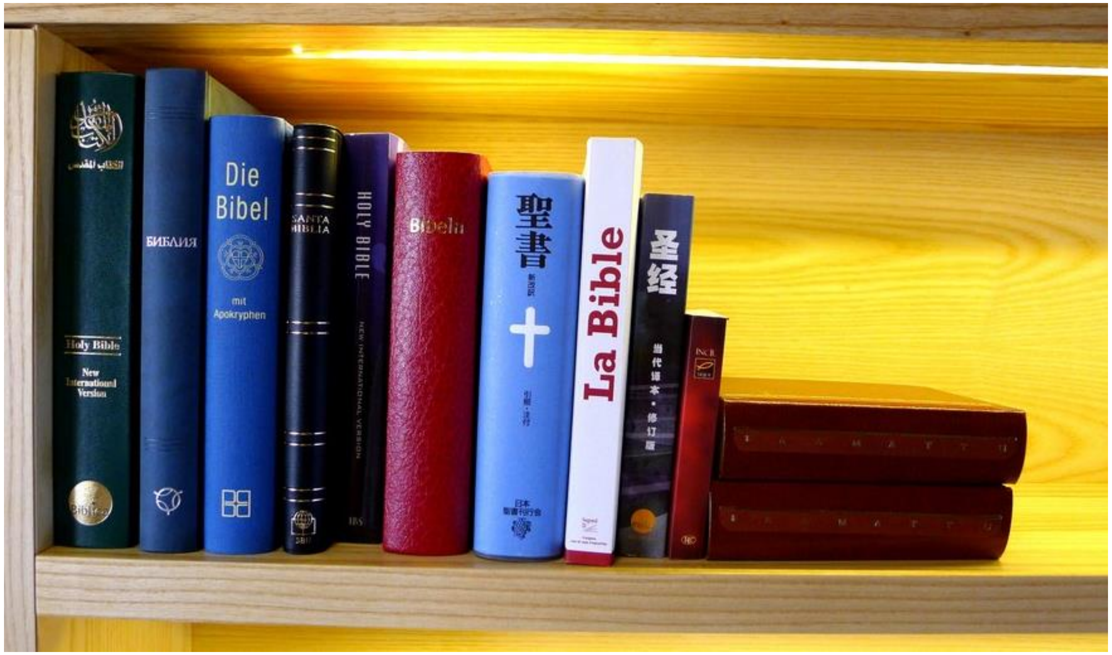
Adapted from Y. Tsvetkov

Multilingual models

- Plain model transfer
  - Scherrer & Rabus 2017 (done)
- Character embeddings + adaptation
  - Cotterell & Heigold 2017 (done)
- Annotation projection
  - Agić et al. 2015
- Delexicalization
  - McDonald et al. 2011
  - Ammar et al. 2016

If all you have is a bit of the Bible...

- Ž. Agić, D. Hovy, A. Søgaard (2015): *If all you have is a bit of the Bible: Learning POS taggers for truly low-resource languages.* ACL 2015.



http://www.domnik.net/photos/kuvia/000/big/006/51-kampinkappeli.jpg

If all you have is a bit of the Bible...

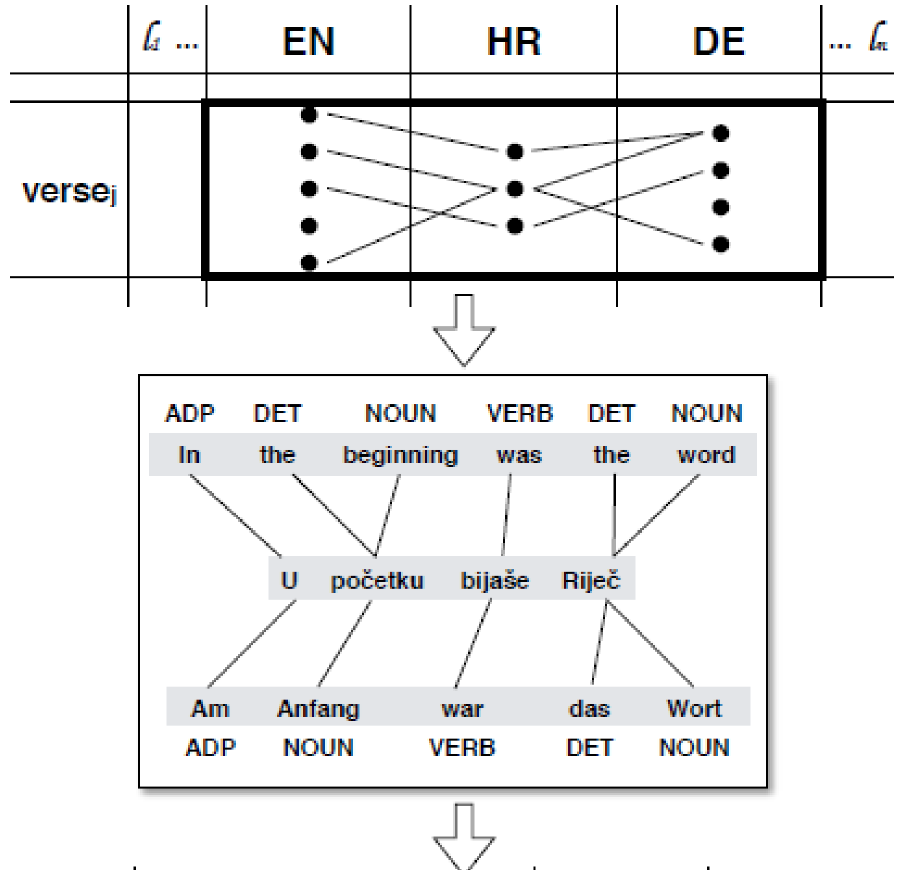
- Ž. Agić, D. Hovy, A. Søgaard (2015): *If all you have is a bit of the Bible: Learning POS taggers for truly low-resource languages.*
- Motivation:

  - stepping into a *truly* under-resourced environment
    - let's take nothing for granted
      - language relatedness
      - huge multi-parallel corpora such as Europarl
      - perfect (or any) preprocessing
    - and still try to provide and evaluate POS taggers for as many under-resourced languages as possible

If all you have is a bit of the Bible…

- Translations of parts of the Bible exist for a huge number of languages:
  - Edinburgh Bible parallel corpus: 100 languages [used here] http://homepages.inf.ed.ac.uk/s0787820/bible/
  - Parallel bible corpus: 1169 languages/varieties http://paralleltext.info/data/
  - Web sources: 1646 languages http://www.bible.is/
- Sentence alignments are easy to obtain: verse IDs
- Split into *k* high-resource languages and *m* low-resource languages, project from all *k* to all *m*: **multi-source projection**

If all you have is a bit of the Bible...



HR	EN	DE	...	voted	confidence
U	ADP	ADP	...	ADP	0.8667
početku	NOUN, DET	NOUN	...	NOUN	0.7448
bijaše	VERB	VERB	...	VERB	0.8560
Riječ	DET, NOUN	DET, NOUN	...	NOUN	0.6307

If all you have is a bit of the Bible…

- Iterative process:
    1. Tag the *k* high-resource language Bibles.
       Project tags from *k* languages to *m* languages.
       Choose tags by majority voting.
    2. Train taggers for *m* low-resource languages using the projected data and tag the *m* low-resource languages (self-training).
       Project tags from *(k+m)-1* to other *(k+m)-1* languages.
       Choose tags by majority voting.
    3. Train taggers for *k+m* languages using the projected data.

- *k* = 18 languages, *m* = 82 languages

If all you have is a bit of the Bible...

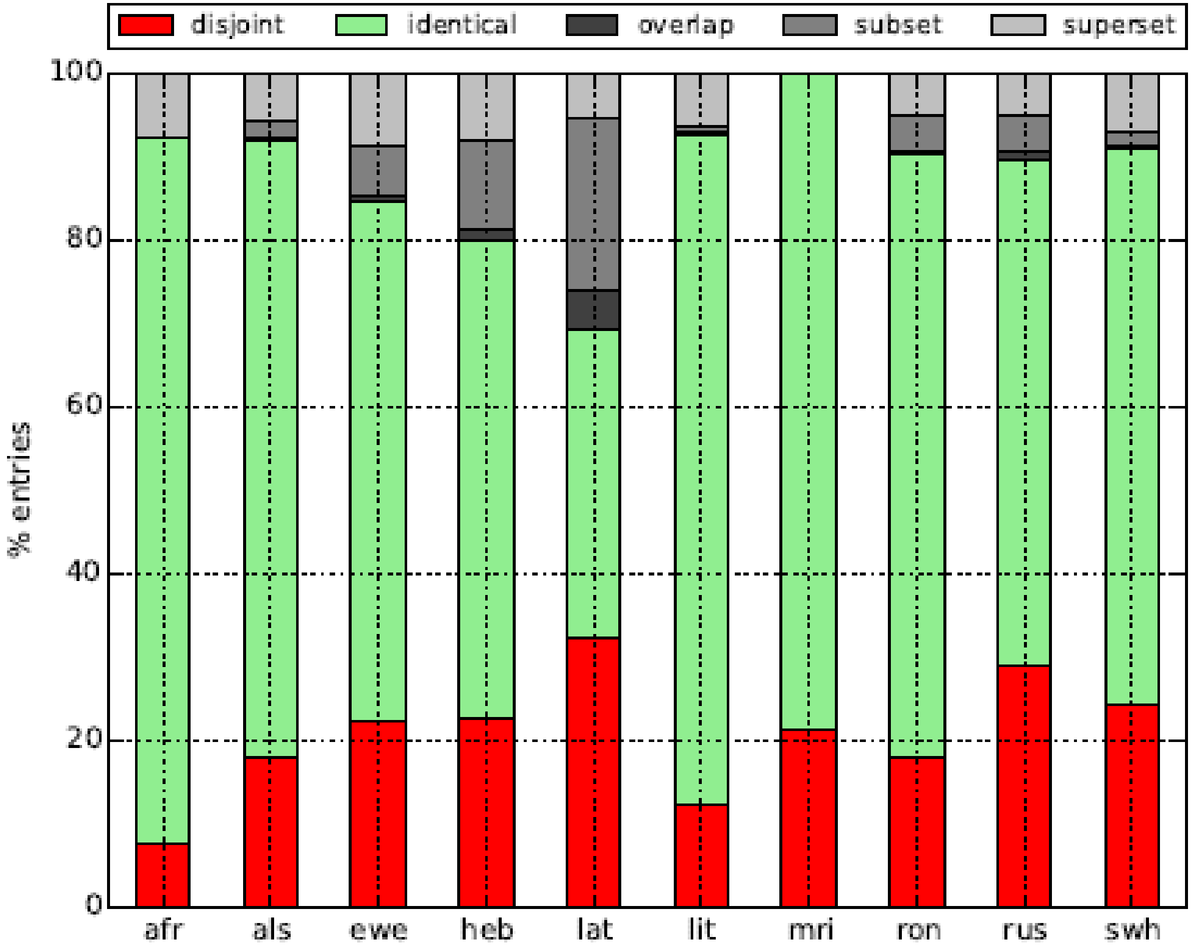
- Low-resource languages include Akawaio, Aukan, Cakchiquel, Ewe, Haitian Creole, Manx, Maori, Somali, Ukrainian, ...

- How do you evaluate this?
  - Test sets available for 25 languages
  - Wiktionary data available for 10 more languages
    → Compute to what extent the projected tag dictionaries overlap with the Wiktionary data

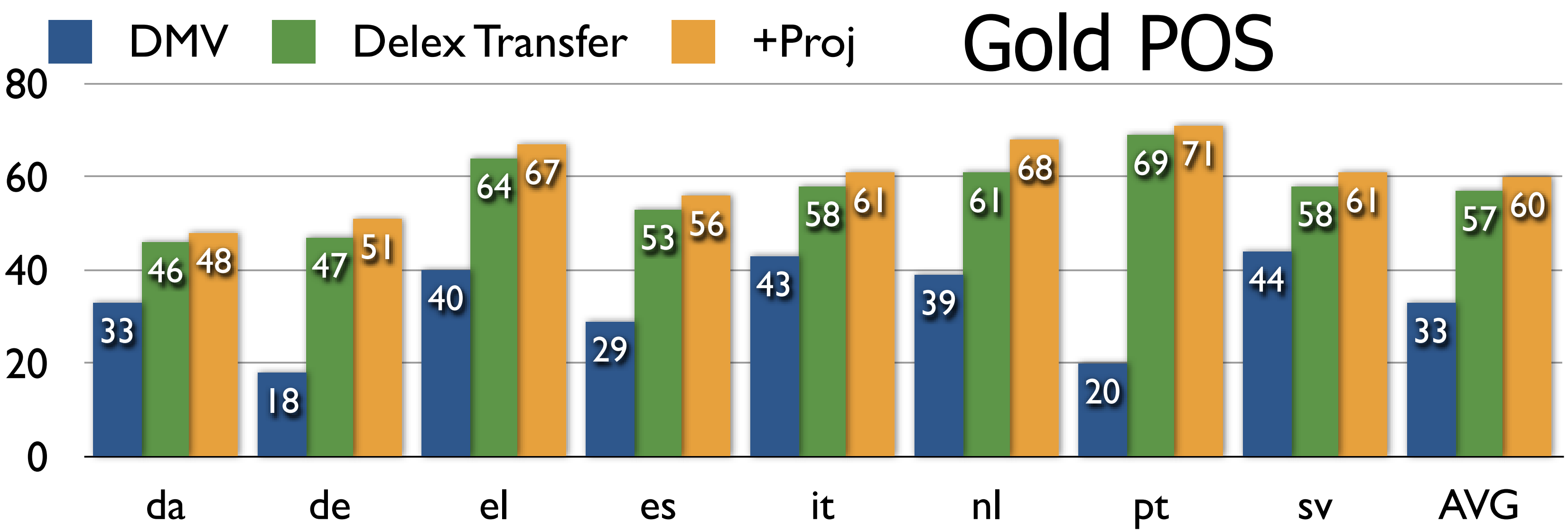
			Unsupervised						Upper bounds			
			Baselines		Our Systems				Weakly Sup		Supervised	
		OOV	Brown	2HMM	TnT-k-Src	TnT-n-1-Src	Gar-k-Src	Gar-n-1-Src	Das	Li	Gar	TnT
bul	YT	31.8	54.5	71.8	**78.0**	77.7	75.7	75.7	-	-	83.1	96.9
ces	YT	44.3	51.9	66.3	71.7	**73.3**	70.9	71.4	-	-	-	98.7
dan	YT	28.6	58.6	69.6	78.6	**79.0**	73.7	73.3	83.2	83.3	78.8	96.7
deu	YT	36.8	45.3	70.0	**80.5**	80.2	77.6	77.6	82.8	85.8	87.1	98.1
eng	YT	38.0	58.2	62.6	72.4	**73.0**	72.2	72.6	-	87.1	80.8	96.7
eus	NT	64.6	46.0	41.6	**63.4**	62.8	57.3	56.9	-	-	66.9	93.7
fra	YT	26.1	42.0	76.5	76.1	76.6	78.6	**80.2**	-	-	85.5	95.1
ell	YT	63.7	43.0	49.8	51.9	52.3	57.9	**59.0**	82.5	79.2	64.4	-
hin	Y	36.1	59.5	69.2	**70.9**	67.6	70.8	71.5	-	-	-	-
hrv	Y	34.7	52.8	65.6	**67.8**	67.1	67.2	66.7	-	-	-	-
hun	YT	41.2	45.9	57.4	70.0	70.4	71.3	**72.0**	-	-	77.9	95.6
isl	Y	19.7	42.6	65.9	**70.6**	69.0	68.7	68.3	-	-	-	-
ind	YT	29.4	52.6	73.1	76.6	**76.8**	74.9	76.0	-	-	87.1	95.1
ita	YT	24.0	45.1	78.3	76.5	76.9	78.5	**79.2**	86.8	86.5	83.5	95.8
plt	Y	35.0	48.9	44.3	56.4	56.6	62.0	**64.6**	-	-	-	-
mar	Y	33.0	**55.8**	45.8	52.0	52.9	52.8	52.3	-	-	-	-
nor	YT	27.5	56.1	73.0	**77.0**	76.7	75.4	76.0	-	-	84.3	97.7
pes	Y	33.6	57.9	**61.5**	59.3	59.6	59.1	60.8	-	-	-	-
pol	YT	36.4	52.2	68.7	**75.6**	75.1	70.8	74.0	-	-	-	95.7
por	YT	27.9	54.5	74.3	82.9	**83.8**	81.1	82.0	87.9	84.5	87.3	96.8
slv	Y	15.8	42.1	78.1	79.5	**80.5**	68.7	70.1	-	-	-	-
spa	YT	21.9	52.6	47.3	81.1	81.4	**82.6**	**82.6**	84.2	86.4	88.7	96.2
srp	Y	41.7	59.3	47.3	**69.6**	69.2	67.9	67.2	-	-	-	94.7
swe	YT	31.5	58.5	68.4	74.7	**75.2**	71.4	71.9	80.5	86.1	76.1	94.7
tur	YT	41.6	53.7	46.8	60.5	**61.3**	56.5	57.9	-	-	72.2	89.1
average		≤ 50	52.2	64.4	72.1	72.2	70.8	71.5				

Evaluation

Figure 2: Type-level in-vocabulary tag errors as the percentage of word types assigned a set of tags that is disjoint, identical to, overlaps, is a subset, or is a superset of the Wiktionary tags.



McDonald et al. 2011



- Blue: irrelevant here
- Green: delexicalized parser trained on English
- Yellow: delexicalized parser trained on English, corrected by annotations projected from English

McDonald et al. 2011

- Is English always the best choice as a source language?

	best-source		avg-source	gold-POS		pred-POS	
	source	gold-POS	gold-POS	multi-dir.	multi-proj.	multi-dir.	multi-proj.
da	it	48.6	46.3	48.9	49.5	46.2	47.5
de	nl	55.8	48.9	56.7	56.6	51.7	52.0
el	en	63.9	51.7	60.1	65.1	58.5	63.0
es	it	68.4	53.2	64.2	64.5	55.6	56.5
it	pt	69.1	58.5	64.1	65.0	56.8	58.9
nl	el	62.1	49.9	55.8	65.7	54.3	64.4
pt	it	74.8	61.6	74.0	75.6	67.7	70.3
sv	pt	66.8	54.8	65.3	68.0	58.3	62.1
avg		63.7	51.6	61.1	63.8	56.1	59.3

McDonald et al. 2011

- It is difficult to choose the optimal source language… Why not use all source languages?
  - multi-dir: all languages except the target language, direct transfer (delexicalized)

	best-source		avg-source	gold-POS		pred-POS	
	source	gold-POS	gold-POS	multi-dir.	multi-proj.	multi-dir.	multi-proj.
da	it	48.6	46.3	48.9	49.5	46.2	47.5
de	nl	55.8	48.9	56.7	56.6	51.7	52.0
el	en	63.9	51.7	60.1	65.1	58.5	63.0
es	it	68.4	53.2	64.2	64.5	55.6	56.5
it	pt	69.1	58.5	64.1	65.0	56.8	58.9
nl	el	62.1	49.9	55.8	65.7	54.3	64.4
pt	it	74.8	61.6	74.0	75.6	67.7	70.3
sv	pt	66.8	54.8	65.3	68.0	58.3	62.1
avg		63.7	51.6	61.1	63.8	56.1	59.3

McDonald et al. 2011

- It is difficult to choose the optimal source language… Why not use all source languages?
  - multi-proj: all languages except target language, with projection

	best-source		avg-source	gold-POS		pred-POS	
	source	gold-POS	gold-POS	multi-dir.	multi-proj.	multi-dir.	multi-proj.
da	it	48.6	46.3	48.9	49.5	46.2	47.5
de	nl	55.8	48.9	56.7	56.6	51.7	52.0
el	en	63.9	51.7	60.1	65.1	58.5	63.0
es	it	68.4	53.2	64.2	64.5	55.6	56.5
it	pt	69.1	58.5	64.1	65.0	56.8	58.9
nl	el	62.1	49.9	55.8	65.7	54.3	64.4
pt	it	74.8	61.6	74.0	75.6	67.7	70.3
sv	pt	66.8	54.8	65.3	68.0	58.3	62.1
avg		63.7	51.6	61.1	63.8	56.1	59.3

Multilingual models???

- The models presented up to here use multiple high-resource languages to annotate a single low-resource language
  - For the Bible model, *k+m* distinct taggers are trained

- Can we create a single unified model that is able to tag/parse several (low-resource) languages?

W. Ammar et al. (2016): *Many languages, one parser*. TACL 4, 2016, 431-444.

Many languages – one parser

- Basic model:
  - Model transfer with language-independent word representations
- What do we need?
  - Treebanks in all source languages with consistent annotations (UD)
  - Multilingual word embeddings
  - Multilingual word clusters
  - Consistent POS tag annotation for delexicalization
  - Language-specific information

Many languages – one parser

- How should NOUN ADJ NOUN be parsed?
  - Some training examples contain prenominal adjectives, some contain postnominal adjectives
  - Depends on the proportion of examples
  - But it should depend on the test language…
- Proposed solution:
  - Label each word (during training and testing) with a language label
  - The model embeds the language labels, so syntactically similar languages should end up having similar language embeddings

Many languages – one parser

- Evaluated on DE, EN, ES, FR, IT, PT, SV
- Three scenarios:
  - **Big treebank:**
    Use complete treebanks from all languages, including test language (supervised scenario)
  - **Small treebank:**
    Use full English treebank + reduced treebank of the test language (3000 tokens, adaptation scenario)
  - **No treebank:**
    Use treebank from all languages excluding test language (low-resource language scenario)

Results
Big treebank scenario

LAS	target language							average
	de	en	es	fr	it	pt	sv	
monolingual	**79.3**	**85.9**	83.7	81.7	88.7	85.7	83.5	84.0
MaLOPa	70.4	69.3	72.4	71.1	78.0	74.1	65.4	71.5
+lexical	76.7	82.0	82.7	81.2	87.6	82.1	81.2	81.9
+language ID	78.6	84.2	83.4	**82.4**	**89.1**	84.2	82.6	83.5
+fine-grained POS	78.9	85.4	**84.3**	**82.4**	89.0	**86.2**	**84.5**	**84.3**

- **MaLOPa:** completely delexicalized
- **+lexical:** with multilingual embeddings/clusters
- **+fine-grained POS:** added language-specific morphosyntactic distinctions

Results

- Small treebank scenario:

LAS	target language				
	de	es	fr	it	sv
monolingual	58.0	64.7	63.0	68.7	57.6
Duong et al.	61.8	**70.5**	67.2	71.3	62.5
MaLOPa	**63.4**	**70.5**	**69.1**	**74.1**	**63.4**

- No treebank scenario:

LAS	target language						average
	de	es	fr	it	pt	sv	
Zhang and Barzilay (2015)	54.1	68.3	68.8	69.4	72.5	62.5	65.9
Guo et al. (2016)	55.9	73.0	71.0	71.2	78.6	69.5	69.3
MaLOPa	57.1	74.6	73.9	72.5	77.0	68.1	70.5

Language labels...

- In multilingual models, it is useful to add language labels to guide the model
  - either on each word, or one per sentence
- What happens in the “no treebank” scenario?
  - The label of the test language has not been seen at all during training, and thus is not helpful.
  - What can we do?

Language labels backwards...

- Instead of providing the language labels as input features, force the model to predict the language of each word
  - Predict POS tag + language label: **multitask learning**
  - This forces the model to distinguish between the languages during training
- At test time, no additional input information is required, but language labels will be output
  - In the “no treebank” scenario, these labels may correspond to anything and are not relevant

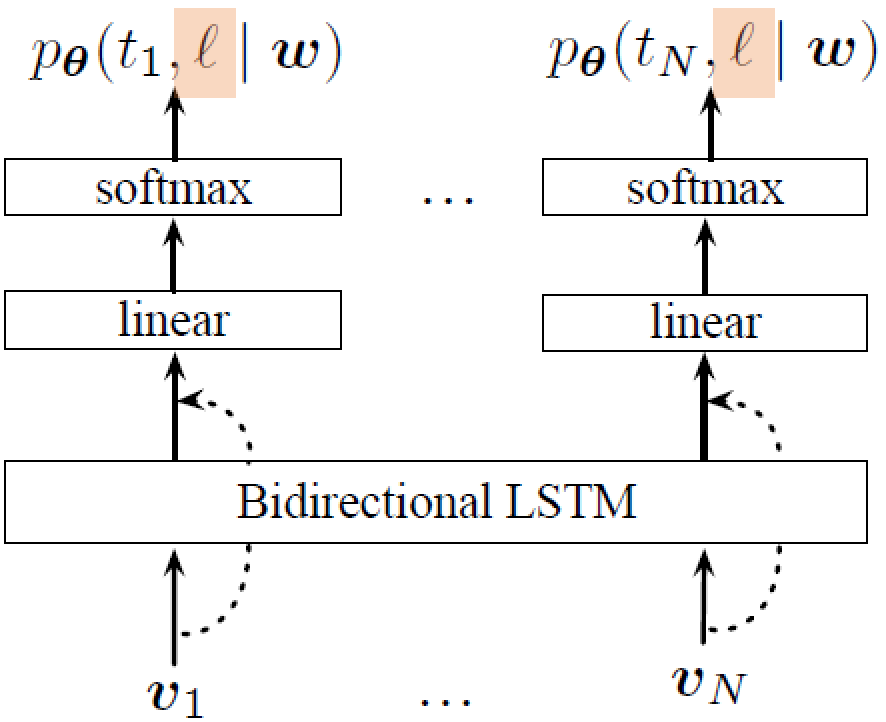
Multitask learning

- What are the conditions for converting an input feature to an **auxiliary task**?
  - Must be learnable from the remaining input features

- Example:
  - A typical parser relies on POS tags as input features
  - Conversion to multitask learning: Learn to predict POS tag and dependency relation at the same time

Multitask learning

- The Cotterell & Heigold tagger actually uses language labels as auxiliary task
- Bilingual model:
  - Source language
  - 100 sentences of target language



(b) Joint morphological tagging and language identification.

What about machine translation?

- Until now, we mostly talked about sequence labeling tasks (tagging, parsing, ...)
- We assumed that MT systems / parallel corpora were more readily available than syntactically annotated corpora
- What if these assumptions do not hold?
  - No parallel data for a particular language pair, but for several other language pairs: **zero-shot translation**
  - No parallel data at all: **unsupervised translation**

Zero-shot machine translation

- Traditional setup:
  - Train a distinct model for each language pair and direction
- Proposed setup:
  - Train a single model for all language pairs and both directions
  - Add target language labels to tell the model what language to translate into

Hello, how are you?
<2es> Hello, how are you?
Hola, ¿cómo estás?

Melvin Johnson et al. (2017): *Google's multilingual neural machine translation system - enabling zero-shot translation*. TACL 5/2017.

Zero-shot machine translation

- Proposed experiment: 12 language pairs
  - English -> Japanese + Japanese -> English
  - English -> Korean + Korean -> English
  - English -> Spanish + Spanish -> English
  - English -> Portuguese + Portuguese -> English
  - English -> German + German -> English
  - English -> French + French -> English
- Does such a multilingual model do better on translating a seen language pair than a standard model?
  - No

Zero-shot machine translation

- Proposed experiment: 12 language pairs
  - English -> Japanese + Japanese -> English
  - English -> Korean + Korean -> English
  - English -> Spanish + Spanish -> English
  - English -> Portuguese + Portuguese -> English
  - English -> German + German -> English
  - English -> French + French -> English
- This model can be used for an unseen language pair:
  - French -> German
  - Spanish -> Japanese ...

Zero-shot machine translation

- Zero-shot translation: No explicit training data from the language pair, but…
  - … the source language has been seen during training (with another target language)
  - … the target language has been seen during training (with another source language)
  - … including multiple language pairs in a single model forces it to build up some abstract representation of a sentence
- Can you think of language pairs for which zero-shot translation could be useful?

Code-switching in source

- **Japanese:** 私は東京大学の学生です。 → I am a student at Tokyo University.
- **Korean:** 나는 도쿄 대학의 학생입니다. → I am a student at Tokyo University.
- **Mixed Japanese/Korean:** 私は東京大学학생입니다. → I am a student of Tokyo University.

Code-mixing in target

Russian/Belarusian:	I wonder what they'll do next!
$w_{be} = 0.00$	Интересно, что они сделают дальше!
$w_{be} = 0.20$	Интересно, что они сделают дальше!
$w_{be} = 0.30$	Цікаво, что они будут делать дальше!
$w_{be} = 0.44$	Цікаво, що вони будуть робити далі!
$w_{be} = 0.46$	Цікаво, що вони будуть робити далі!
$w_{be} = 0.48$	Цікаво, што яны зробяць далей!
$w_{be} = 0.50$	Цікава, што яны будуць рабіць далей!
$w_{be} = 1.00$	Цікава, што яны будуць рабіць далей!

Japanese/Korean:	I must be getting somewhere near the centre of the earth.
$w_{ko} = 0.00$	私は地球の中心の近くにとこかに行っているに違いない。
$w_{ko} = 0.40$	私は地球の中心近くのとこかに着いているに違いない。
$w_{ko} = 0.56$	私は地球の中心の近くのとこかになっているに違いない。
$w_{ko} = 0.58$	私は지구の中心의가까이에어딘가에도착하고있어야한다。
$w_{ko} = 0.60$	나는지구의센터의가까이에어딘가에도착하고있어야한다。
$w_{ko} = 0.70$	나는지구의중심근처어딘가에도착해야합니다。
$w_{ko} = 0.90$	나는어딘가지구의중심근처에도착해야합니다。
$w_{ko} = 1.00$	나는어딘가지구의중심근처에도착해야합니다。

Spanish/Portuguese:	Here the other guinea-pig cheered, and was suppressed.
$w_{pt} = 0.00$	Aquí el otro conejillo de indias animó, y fue suprimido.
$w_{pt} = 0.30$	Aquí el otro conejillo de indias animó, y fue suprimido.
$w_{pt} = 0.40$	Aquí, o outro porquinho-da-índia alegrou, e foi suprimido.
$w_{pt} = 0.42$	Aqui o outro porquinho-da-índia alegrou, e foi suprimido.
$w_{pt} = 0.70$	Aqui o outro porquinho-da-índia alegrou, e foi suprimido.
$w_{pt} = 0.80$	Aqui a outra cobaia animou, e foi suprimida.
$w_{pt} = 1.00$	Aqui a outra cobaia animou, e foi suprimida.

Terminology: Zero-shot learning

- Zero-shot = no training data of the target task
  - Translation: no training data of the language pair
- Zero-shot learning = transfer learning without explicit adaptation to target language
  - All model transfer methods (except relexicalization) can be considered zero-shot learning methods
- In opposition to adaptation models
  - A small amount of training data for the target language is given (cf. Cotterell & Heigold)

Unsupervised machine translation

- What if we don't have parallel data at all?
  - Use monolingual data ☺
  - Use multilingual word/sentence embeddings (built without using parallel data, obviously)

M. Artetxe et al. (2018): *Unsupervised neural machine translation*. Proceedings of ICLR 2018.
G. Lample et al. (2018): *Unsupervised machine translation using monolingual corpora only*. Proceedings of ICLR 2018.

Unsupervised machine translation

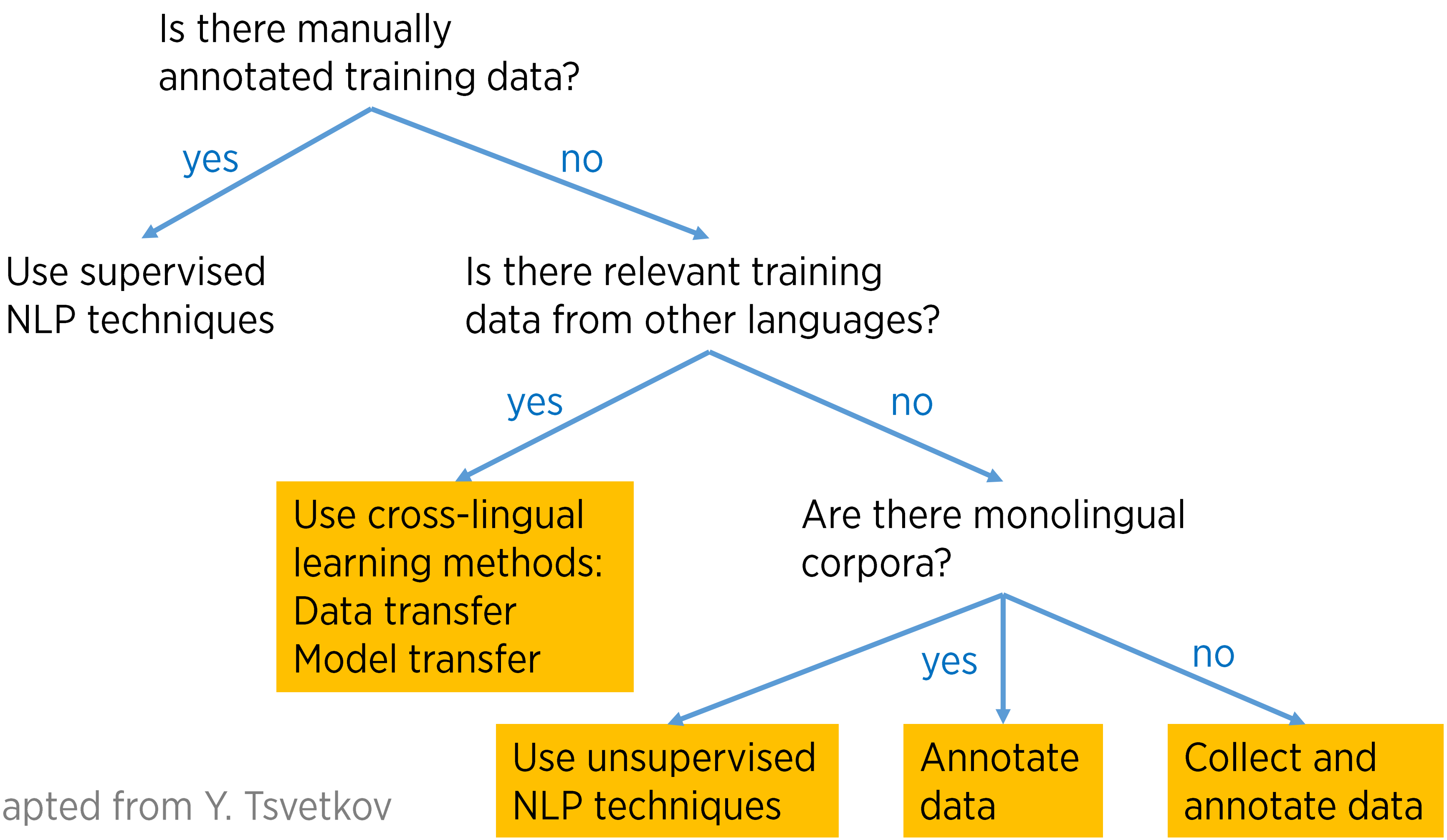
- Use zero-shot learning for paraphrasing:
  - Train on English -> French and French -> English
  - Test on English -> English

- Turn the problem around:
  - Train on English -> English and French -> French
  - Test on English -> French
  - Need to introduce noise in training data to prevent the model from learning to copy-paste
  - Single system, French and English words are represented in the same vector space

How well does that work? Examples from WMT 2018

Source	Supervised	Unsupervised	Reference
München 1856: Vier Karten, die Ihren Blick auf die Stadt verändern	Munich 1856: four maps that change your view of the city	Munich 1856 - four card, changing their look on the city	Munich 1856: Four maps that will change your view of the city
Eine Irren-Anstalt, wo sich heute Jugendliche begegnen sollen.	An insane institution where young people are supposed to meet today.	A Irren-anstalt where teenagers will interact today.	A mental asylum, where today young people are said to meet.
Eine Gruftkapelle, wo nun für den S-Bahn-Tunnel gegraben wird.	A Gruftkapelle, where the S-Bahn tunnel is now being dug.	A Gruftkapelle, where it will now be dug for the S-bahn-tunnel.	A crypt chapel, where they are now digging tunnels for the S-Bahn.
Kleingärtner bewirtschaften den einstigen Grund von Bauern.	Small gardeners manage the former land of farmers.	Gardeners graze the erstwhile reason by farmers.	Allotment holders cultivate the soil of former farmers.
Die älteste offizielle Karte Münchens fördert spannende Geschichten zu Tage.	The oldest official map of Munich reveals exciting stories.	The oldest official cards Ferguson promotes exciting stories to days.	The oldest official map of Munich brings captivating stories to light.

What resources can we get?



Adapted from Y. Tsvetkov

Enjoy the Midsummer weekend!

Hyvää Juhannusta!