Massive Choice, Ample Tasks (MACHAMP):

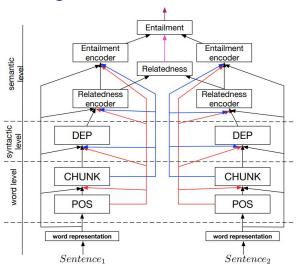


A Toolkit for Multi-task Learning in NLP



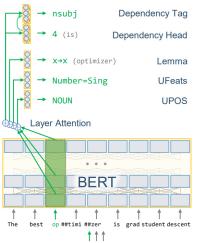
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Multitask Learning



Taken from: A Joint Many-Task Model: Growing a Neural Network for Multiple NLP Tasks. Kazuma Hashimoto, Caiming Xiong, Yoshimasa Tsuruoka, Richard Socher (EMNLP 2017)

Udify



"The best optimizer is grad student descent"

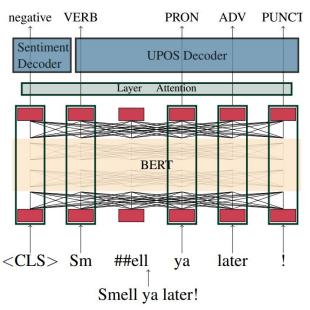
Taken from: 75 Languages, 1 Model: Parsing Universal Dependencies Universally Dan Kondratyuk and Milan Straka (EMNLP 2019)

MaChAmp



One arm alone can move mountains.

MaChAmp



Original research questions

- ► Can it still be beneficial to process tasks sequentially (and embed previous predictions)?
- ▶ What would the best order be?

Input to decoder

Normal case:

b

Input to decoder

Normal case:

b

Add information from previous task prediction:

 $\vec{b} \cdot \vec{l}$

Input to decoder

Normal case:

Ē

Add information from previous task prediction:

$$\vec{b} \cdot \vec{l}$$

Weighted average from previous prediction:

$$\vec{b} \cdot \sum_{i=0}^{n} p_i * \vec{l_i}$$

```
"UD": {
    "train_data_path": "data/ewt.train",
    "validation_data_path": "data/ewt.dev",
    "word_idx": 1,
    "tasks": {
        "upos": {
            "task_type": "seq",
            "column_idx": 3
```

Training can be as easy as:

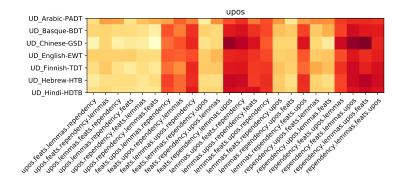
python3 train.py --dataset_config upos.json

Training can also be done like:

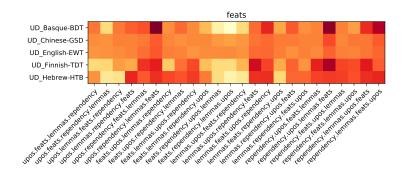
```
python3 train.py --dataset_config upos.json --name \
EWT.upos --device -1 --parameters_config newParams.json
```

```
"UD": {
    "train_data_path": "data/ewt.train",
    "validation_data_path": "data/ewt.dev",
    "word_idx": 1,
    "tasks": {
        "upos": {
            "task_type": "seq",
            "column_idx": 3
        "xpos": {
            "task_type": "seq",
            "column_idx": 4,
            "prev_task_embed_dim":32,
            "order":2
```

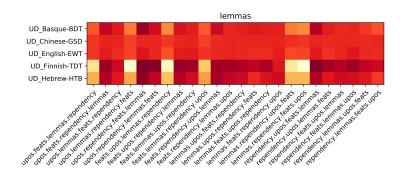
Multiple languages (UPOS)



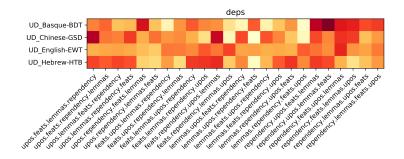
Multiple languages (Morphological tagging)



Multiple languages (Lemmas)



Multiple languages (Dependency parsing)



Comparison to previous work

	$\rm JMT_{all}$	Random
POS	97.88	97.83
Chunking	97.59	97.71
Dependency UAS	94.51	94.66
Dependency LAS	92.60	92.80
Relatedness	0.236	0.298
Entailment	84.6	83.2

Taken from: A Joint Many-Task Model: Growing a Neural Network for Multiple NLP Tasks. Kazuma Hashimoto, Caiming Xiong, Yoshimasa Tsuruoka, Richard Socher (EMNLP 2017)





Now what?

So, how about using word-level tasks to improve phrase-level tasks?

Now what?

So, how about using word-level tasks to improve phrase-level tasks?

- Add sentence level tasks (and make it possible to use multiple datasets simultaneously)
- ► Make challenging: cross-lingual settings!

```
"UD": {
    "train_data_path": "data/ewt.train",
    "validation_data_path": "data/ewt.dev",
    "word_idx": 1,
    "tasks": {
        "upos": {
            "task_type": "seq",
            "column_idx": 3
        },
},"RTE" {
    "train_data_path": "data/ewt.train",
    "validation_data_path": "data/ewt.dev",
    "sent_idxs": [0,1],
    "tasks": {
        "rte": {
            "task_type": "classification",
            "column_idx": 2
        },
```

Task Types

- ▶ seq
- string2string
- dependency
- multiseq
- masked_crf
- classification

Task Types

- seq
- string2string
- dependency
- multiseq
- masked_crf
- classification



Performance

- ► EWT
- ► PMB
- ► GLUE



EWT v2.3				PMB v3.0					
dep	feats	lemma	upos	xpos	lemma	semtag	supertag	verbnet	wordnet
dep	seq	s2s	seq	seq	s2s	seq	seq	seq	s2s
		205k					43k		
89.90	97.18	98.21	97.01	96.64	97.52	98.32	94.87	94.37	89.15
89.61	97.15	97.79	97.01	96.79	97.33	98.23	94.91	94.54	89.32
89.67	97.15	97.80	96.90	-	_	_	_	_	-
	dep 89.90 89.61	dep feats dep seq 89.90 97.18 89.61 97.15	dep dep dep dep seq feats seq s2s 205k 89.90 97.18 98.21 89.61 97.15 97.79	dep dep dep dep feats seq seq s2s seq 205k lemma seq seq seq seq seq 205k 89.90 97.18 98.21 97.01 89.61 97.15 97.79 97.01	dep dep dep dep dep dep seq feats seq s2s seq seq 205k upos seq seq seq seq seq seq seq seq seq se	dep	dep	dep dep dep dep seq feats seq lemma seq seq seq seq xpos seq seq lemma semtag supertag seq supertag seq 89.90 97.18 98.21 97.01 96.64 97.52 98.32 94.87 89.61 97.15 97.79 97.01 96.79 97.33 98.23 94.91	dep dep dep seq feats seq lemma seq xpos seq lemma semtag supertag supertag verbnet 89.90 97.18 98.21 97.01 96.64 97.52 98.32 94.87 94.37 89.61 97.15 97.79 97.01 96.79 97.33 98.23 94.91 94.54

		GLUE							
Task	cola	mnli	mnli-mis	mrpc	qnli	qqp	rte	snli	sst-2
Task type	С	С	С	С	С	С	С	С	С
Train size	8.5k	392k	392k	3.6k	108k	363k	2.5k	549k	67k

86.03

82.11

88.31

86.58

89.75

89.27

72.20

73.65

89.58

89.61

93.3

90.71

90.25

82.15

82.80

86.7

 $MACHAMP_{(ST)}$

 $MACHAMP_{(MT)}$

BERT-base

78.04

72.20

81.99

82.35

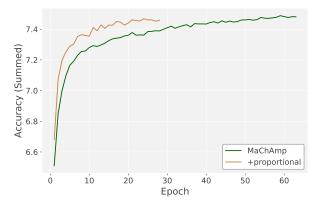
84.4

Proportional sampling

- Downscale each task to the smallest task
- Upscale each task to the largest task
- ► Take the average amount of batches over all tasks for all tasks

Proportional sampling

- Downscale each task to the smallest task
- Upscale each task to the largest task
- Take the average amount of batches over all tasks for all tasks



Zero-shot learning

Preliminary Results

	English	Arabic	Turkish	Urdu	Vietnamese
En-XNLI	81.84	65.93	61.52	58.02	69.08
En-XNLI +En-UD +X-UD	-	63.17 Wo: 0.64/0.30	60.56 WO: 0.52/0.19	59.72 WO: 0.76/0.31	67.65 WO: 0.70/0.22
En-XNLI +X-UD (4 Tasks)		64.57 wo: 0.64/0.30	59.39 WO: 0.49/0.17	58.75 wo: 0.76/0.27	70.02 WO: 0.68/0.15

Natural language understanding

```
set a reminder to tell my wife i love her O O B-Rem./NN O B-Rem. I-R I-R I-R I-R
```

Intent: setReminder

Natural language understanding

```
# text: Set alarm every minute for next hour
 intent: alarm/set_alarm
 slots: 10:36:datetime
1
        set
                alarm/set_alarm NoLabel
        alarm alarm/set_alarm NoLabel
2
3
        every alarm/set_alarm B-datetime
4
        minute alarm/set_alarm I-datetime
5
                alarm/set_alarm I-datetime
        for
6
                alarm/set_alarm I-datetime
        next.
        hour
                alarm/set_alarm I-datetime
```

Natural language understanding

```
"NLU": {
    "train_data_path": "data/nlu/train-en.conllu",
    "validation_data_path": "data/nlu/eval-en.conllu",
    "word_idx": 1,
    "tasks": {
        "slot": {
            "task_type": "seq",
            "metric": "span-f1",
            "column_idx": 3
        },
        "intent": {
            "task_type": "classification",
            "column_idx": -1
```

NLU (zero-shot ES)

model	intents	slots	exact
schuster-translate	85.39	72.87	54.95
schuster-cove	53.34	22.50	10.56

NLU (zero-shot ES)

model	intents	slots	exact
schuster-translate	85.39	72.87	54.95
schuster-cove	53.34	22.50	10.56
MaChAmp-NLU	84.21	75.01	56.02
MaChAmp-NLU-UD-sep	84.77	70.79	48.41
MaChAmp-NLU-UD-mixed	87.79	71.01	48.10

Results from: Cross-lingual Transfer Learning for Multilingual Task Oriented Dialog. Sebastian Schuster, Sonal Gupta, Rushin Shah, and Mike Lewis (NAACL 2019)

Other things this framework has been used for:

- ▶ POS tagging for code-switched data
- Biomedical event extraction
- ▶ Rik: effect of PMB predictions on Boxer performance
- ► Inspect BERT layer performances for UD tasks
- Nested named entity tagging for Danish
- Lexical normalization

Smell you later!



Multiple languages (UPOS)

