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Intro to *Flair*: Open Source NLP Framework

Alan Akbik

Zalando Research

Berlin ML Meetup,
December 2018

TEXT DATA IN FASHION

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www.cocoandvera.com

[...] How I style the basics that fill my wardrobe changes from season to season. And city to city, too, come to think of it. In Berlin, I paired this dress with a moto jacket and ankle boots, while in Paris, I added an oversized hat and classic pumps. [...]

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★★★★★

O yes very comtable soft leather please sell them in Red

★★★★★

I absolutely love these shoes. Smart but casual. Very comfortable. I might buy a second pair.

TEXT DATA IN FASHION

Levis t-shirts for men

[...] How I style the basics that fill my wardrobe changes from season to season. And city to city, too, come to think of it. In Berlin, I paired this dress with a moto jacket and ankle boots, while in Paris, I added an oversized hat and classic pumps. [...]

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DOCUMENT CLASSIFICATION

Document 1

[...] quick delivery as always. Thank you very much! [...]

Document 2

[...] waited for three days until the package finally arrived! [...]

Task: automatically categorize your documents into one or more classes

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Classes

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DELIVERY-SLOW

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Document 2 → DELIVERY-SLOW

Task: automatically categorize your documents into one or more classes

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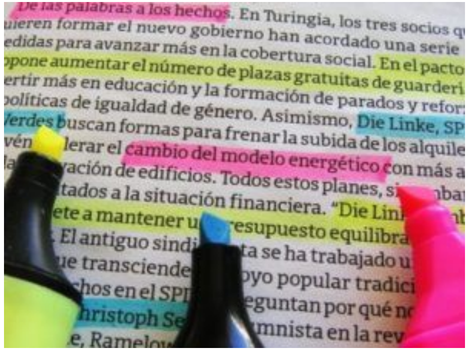
SEQUENCE LABELING



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Fashion Entity Types

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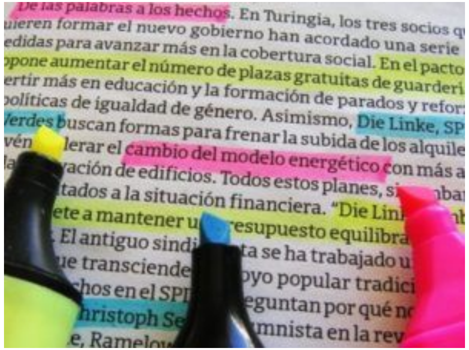

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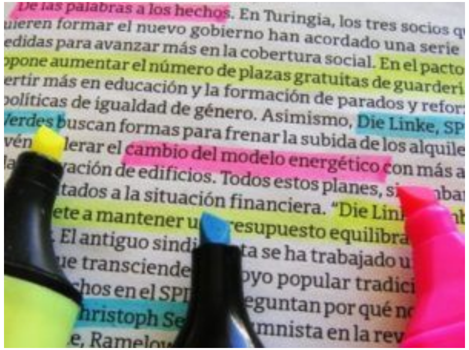

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Fashion Entity Types

NamedLocation NominalProduct

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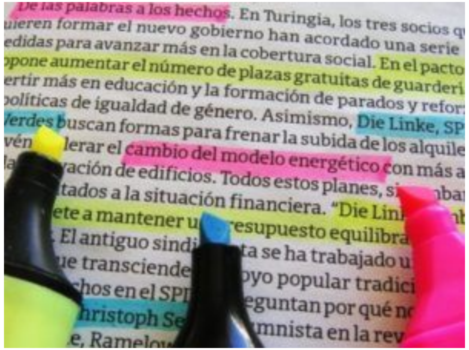

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Fashion Entity Types

NamedLocation NominalProduct NamedPerson

NamedOrganizationRetailer

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FLAIR FRAMEWORK

flair

a *very simple* framework for *state-of-the-art* natural language processing (NLP)

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- current **state-of-the-art** across many NLP tasks

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flair

a *very simple* framework for *state-of-the-art* natural language processing (NLP)

- current **state-of-the-art** across many NLP tasks
- **very simple** to use

THIS TALK

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1. New type of word embeddings

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2. New state-of-the-art scores across sequence labeling tasks

Task	Our approach	Previous best
NER English	**93.09** ± 0.12	92.22±0.1 (Peters et al., 2018)
NER German	**88.32** ± 0.2	78.76 (Lample et al., 2016)
Chunking	**96.72** ± 0.05	96.37±0.05 (Peters et al., 2017)
PoS tagging	**97.85** ± 0.01	97.64 (Choi, 2016)

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3. Introduce **Flair framework**

Talk Outline

Overview

Flair Embeddings

Limitations of classic word embeddings

Character-level neural language models

Comparative evaluation

Flair Framework

Usage Example

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Talk Outline

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Usage Example

WORD EMBEDDINGS

Classic word embeddings learn a vector representation for each word in a fixed vocabulary

WORD EMBEDDINGS

Problem: Words are just strings

Vocabulary:
Man, woman, boy, girl, prince, princess, queen, king, monarch

	1	2	3	4	5	6	7	8	9
man	1	0	0	0	0	0	0	0	0
woman	0	1	0	0	0	0	0	0	0
boy	0	0	1	0	0	0	0	0	0
girl	0	0	0	1	0	0	0	0	0
prince	0	0	0	0	1	0	0	0	0
princess	0	0	0	0	0	1	0	0	0
queen	0	0	0	0	0	0	1	0	0
king	0	0	0	0	0	0	0	1	0
monarch	0	0	0	0	0	0	0	0	1

Each word gets a 1x9 vector representation

WORD EMBEDDINGS

Try to build a lower dimensional embedding

Vocabulary:
Man, woman, boy, girl, prince, princess, queen, king, monarch

	Femininity	Youth	Royalty
Man			
Woman			
Boy			
Girl			
Prince			
Princess			
Queen			
King			
Monarch			

@shane_a_lynn | @TeamEdgeTier

22

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Girl	1	1	0
Prince	0	1	1
Princess	1	1	1
Queen	1	0	1
King	0	0	1
Monarch	0.5	0.5	1

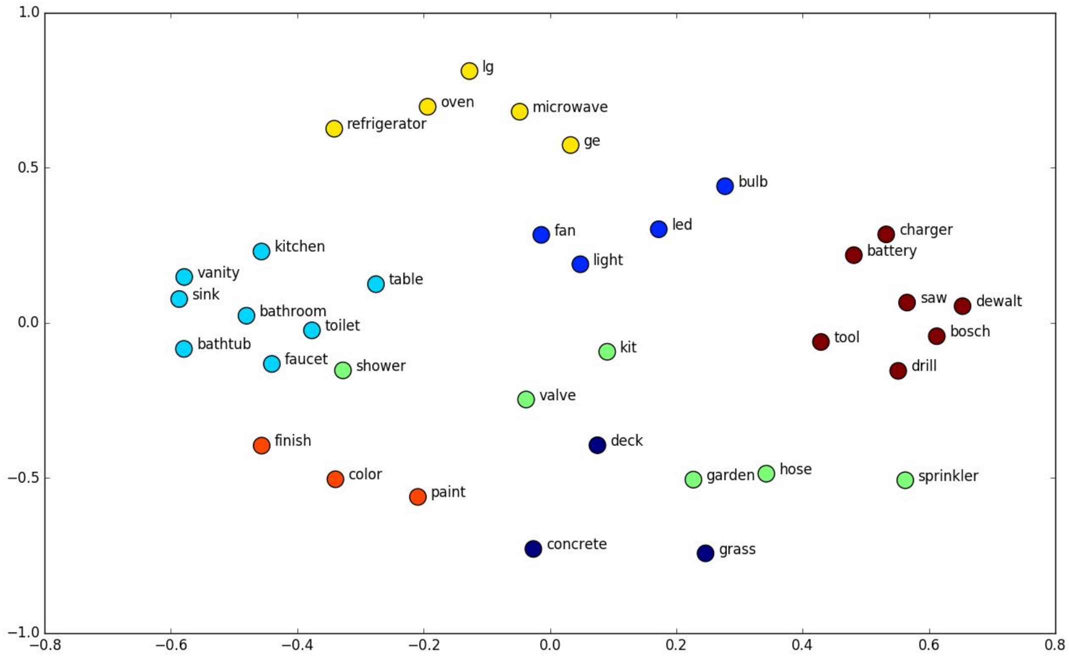
Each word gets a 1x3 vector

Similar words... similar vectors

@shane_a_lynn | @TeamEdgeTier

WORD EMBEDDINGS

Classic word embeddings learn a vector representation for each word in a fixed vocabulary



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- "Washington"
  - Last name
  - State / city
  - Sports team
  - …

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  - Rare words?
  - Out of vocabulary words?
  - “coooooooool”

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  - Out of vocabulary words?
  - "cooooooool"
- Meaningful embeddings for any word?

CONTEXTUAL STRING EMBEDDINGS

We propose **contextual string embeddings** that are:

- *Contextualized* by their usage in text

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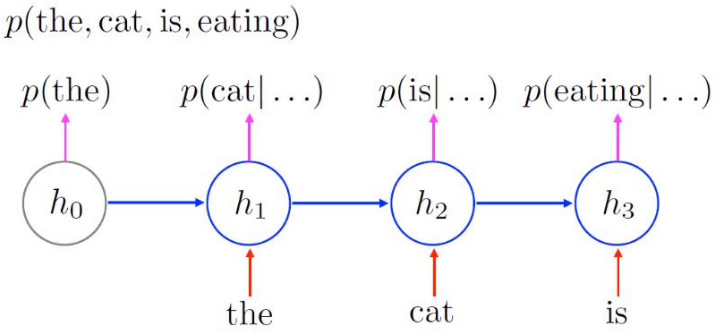
We produce these embeddings using **neural character-level language modeling**

NEURAL LANGUAGE MODELING

Language modeling:

- Train recurrent neural network (RNN) to predict the next word in a sequence of words



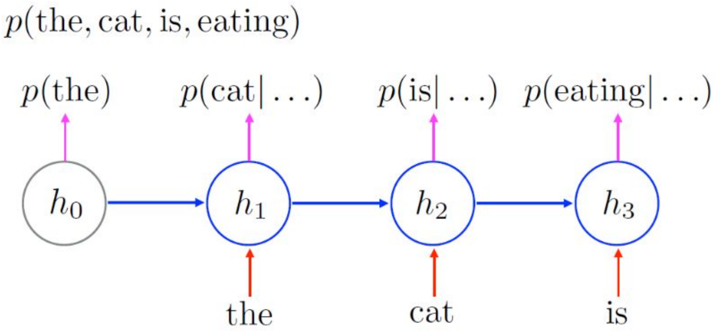
NEURAL LANGUAGE MODELING

Language modeling:

- Train recurrent neural network (RNN) to predict the next word in a sequence of words

Character-level language modeling:

- Train RNN to predict the next *character* in a sequence of *characters*
- No tokenization
- Small vocabulary



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NEURAL LANGUAGE MODELING

what is the next word?

because it was hungry, the cat ___

NEURAL LANGUAGE MODELING

what is the next word?

because it was hungry, the cat ___   ***ate***

NEURAL LANGUAGE MODELING

what is the next word?

because it was hungry, the cat ___ ***ate***

what is the next word?

because it was hungry, the cat ate ____

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what is the next word?

because it was hungry, the cat ___ **_ate_**

what is the next word?

because it was hungry, the cat ate ____ **_the_**

what is the next word?

because it was hungry, the cat ate the ____

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what is the next word?

because it was hungry, the cat ___

ate

what is the next word?

because it was hungry, the cat ate ____

the

what is the next word?

because it was hungry, the cat ate the ____

The model learns

- Shallow syntax
  - nouns, verbs, adjectives
  - tense, number
- Sentence-level syntax
  - constituents
  - subordinate clauses
  - punctuation, capitalization
- Shallow semantics
  - sentiment
  - topic

WHAT DOES THIS NEURAL LANGUAGE MODEL KNOW?

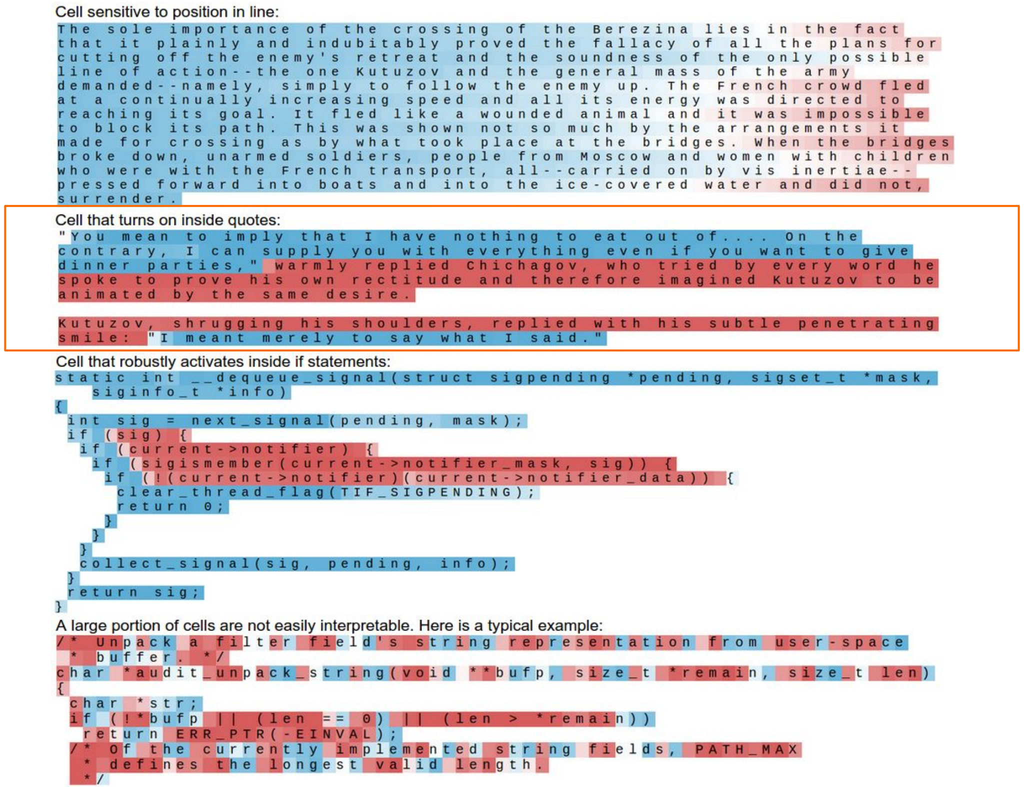
We can sample the LM to **generate text**:

(1) According to a giant external film crew , the visible food contained " weirdness or unknown " firestorms .

(2) According to ADA attorney Stacy Baileil , prosecutors have requested that all of the county bend to him rather than require him to accept the legal fees .

(3) Iran 's Deputy Marine Ministry inspector general last week criticised security forces for testing changes in a military base when attackers began putting metal plates in , he said .

INTERNAL LM REPRESENTATIONS



Model represents syntactic and semantic properties!

(Radfort et. al, 2017)

PROPOSED APPROACH

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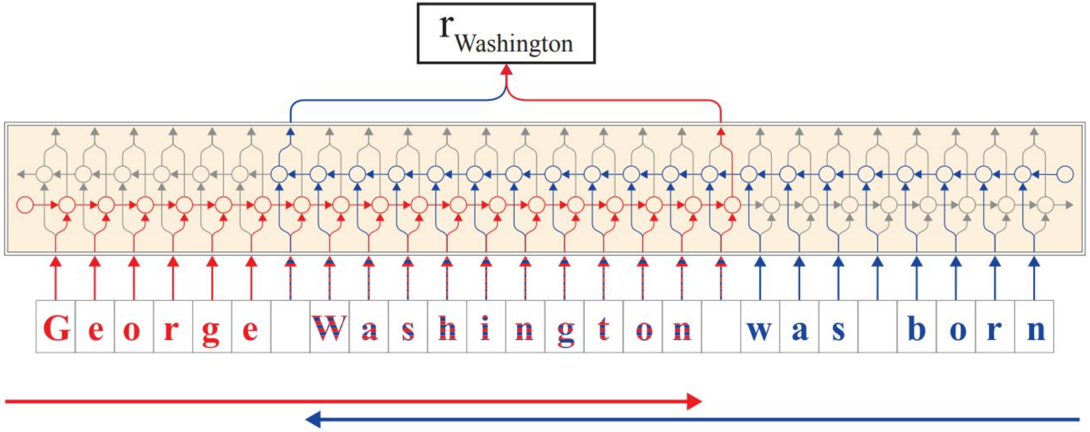

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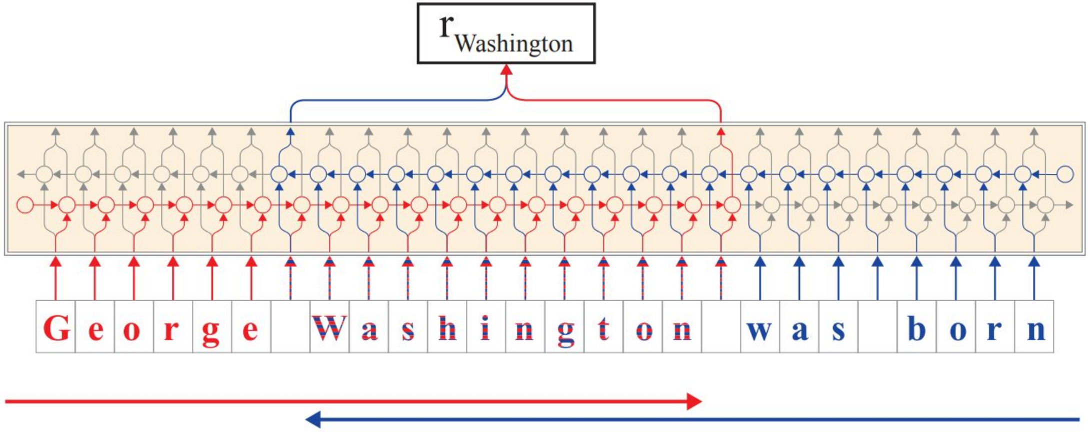
PROPOSED APPROACH



- Pass sentence as sequence of characters into two character-level language models
- Retrieve the internal states before first and after last character for each word
- Combine forward and backward states to form embedding

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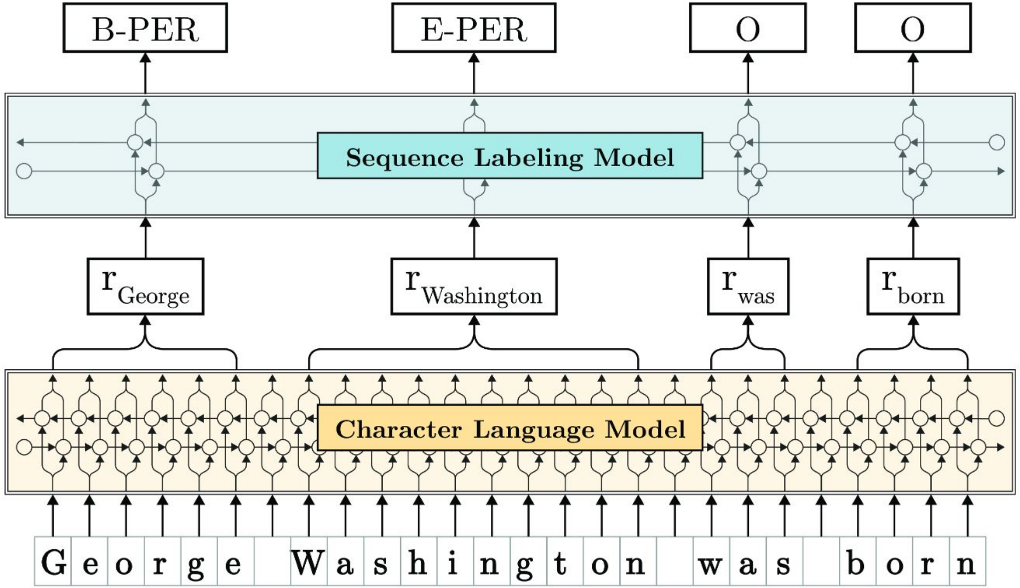
TRANSFER LEARNING



Supervised task

Unsupervised task

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COMPARATIVE EVALUATION

Tasks:

- CoNLL-03 Named Entity Recognition for English and German
- CoNLL-2000 Chunking
- WSJ Part-of-Speech Tagging

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Tasks:

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Setup:

- BiLSTM-CRF architecture (Huang et. al, 2015)
    - Only classic word embeddings (Huang et. al, 2015)
    - Word and character embeddings (Lample et. al, 2016)
    - **ELMo embeddings** (Peters et. al, 2017; 2018)

RESULTS

Approach	NER-English F1-score	NER-German F1-score	Chunking F1-score	POS Accuracy
proposed				
PROPOSED	91.97±0.04	85.78 ± 0.18	96.68±0.03	97.73±0.02
PROPOSED+WORD	93.07±0.10	88.20 ± 0.21	96.70±0.04	97.82±0.02
PROPOSED+CHAR	91.92±0.03	85.88 ± 0.20	**96.72**±0.05	97.8±0.01
PROPOSED+WORD+CHAR	**93.09**±0.12	**88.32** ± 0.20	96.71±0.07	97.76±0.01
PROPOSED+ALL	92.72±0.09	n/a	96.65±0.05	**97.85**±0.01
baselines				
HUANG	88.54±0.08	82.32 ± 0.35	95.4±0.08	96.94±0.02
LAMPLE	89.3±0.23	83.78 ± 0.39	95.34±0.06	97.02±0.03
PETERS	92.34±0.09	n/a	96.69±0.05	97.81± 0.02
best published				
	92.22±0.10 (Peters et al., 2018)	78.76 (Lample et al., 2016)	96.37±0.05 (Peters et al., 2017)	97.64 (Choi, 2016)
	91.93±0.19 (Peters et al., 2017)	77.20 (Seyler et al., 2017)	95.96±0.08 (Liu et al., 2017)	97.55 (Ma and Hovy, 2016)
	91.71±0.10 (Liu et al., 2017)	76.22 (Gillick et al., 2015)	95.77 (Hashimoto et al., 2016)	97.53±0.03 (Liu et al., 2017)
	91.21 (Ma and Hovy, 2016)	75.72 (Qi et al., 2009)	95.56 Søgaard et al. (2016)	97.30 (Lample et al., 2016)

EVALUATION RESULTS

Takeaways [1]:

- Combination of Contextual String Embeddings and Classic Word Embeddings consistently gives us state-of-the-art results

[1] Contextual String Embeddings for Sequence Labeling. Alan Akbik, Duncan Blythe, Roland Vollgraf. **27th International Conference on Computational Linguistics, COLING 2018.**

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- Also state-of-the-art for Polish [2]

[1] Contextual String Embeddings for Sequence Labeling. Alan Akbik, Duncan Blythe, Roland Vollgraf. **27th International Conference on Computational Linguistics, COLING 2018.**

[2] Approaching nested named entity recognition with parallel LSTM-CRFs. Łukasz Borchmann, Andrzej Gretkowski, Filip Graliński. **Proceedings of the PolEval 2018 Workshop, PolEval 2018.**

Talk Outline

Overview

Contextual String Embeddings

Limitations of classic word embeddings

Character-level neural language models

Sequence Labeling Experiments

Baselines and experimental setup

Results of comparative evaluation

OPEN SOURCE RELEASE

flair - a very simple framework for state-of-the-art NLP

```
pip install flair
```

Flair is:

- A Python library installable through pip
- Built on Pytorch
- Currently at version 0.3.2

Use Flair to:

- Apply our pre-trained taggers on your text
- Train your own NLP models

TAG A SENTENCE

```
from flair.data import Sentence
from flair.models import SequenceTagger

# make a sentence
sentence = Sentence('I love Berlin .')

# load the NER tagger
tagger = SequenceTagger.load('ner')

# run NER over sentence
tagger.predict(sentence)
```

```
print(sentence)
```

```
Sentence: "I love Berlin ." - 4 Tokens
```

```
print(sentence.to_tagged_string())
```

```
I love Berlin <S-LOC> .
```


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SPAN ANNOTATIONS

```python
# make a sentence
sentence = Sentence('George Washington was born in Washington .')

# run NER over sentence
tagger.predict(sentence)

for entity in sentence.get_spans('ner'):
    print(entity)
```

```
PER-span [1,2]: "George Washington"
LOC-span [5]: "Washington"
```

EMBED A SENTENCE

```
from flair.embeddings import
WordEmbeddings

# init embedding
glove_embedding =
WordEmbeddings('glove')

# create sentence.
sentence = Sentence('The grass is
green .')

# embed a sentence using glove.
glove_embedding.embed(sentence)
```


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FLAIR, ELMO AND BERT EMBEDDINGS

```
# contextual string embeddings
flair_embedding = FlairEmbeddings('news-forward')

# ELMo embeddings (Peters et. al, 2018)
elmo_embedding = ELMoEmbeddings('medium')

# Google’s BERT embeddings (Devlin et. al, 2018)
bert_embedding = BertEmbeddings('large-uncased')

# stacked embeddings
embedding = StackedEmbeddings([flair_embedding, elmo_embedding,
bert_embedding])
```

TRAIN YOUR OWN MODELS

Data fetchers

- Automatically download publicly available NLP datasets
- Data readers for common NLP formats

Model trainer

- Training mechanisms: annealing, checkpointing, restarts, etc.
- Automatic hyperparameter selection

Tutorials online to get you started

JOIN THE TEAM!

flair is on github

Use it

- Install through pip or clone

Help develop it

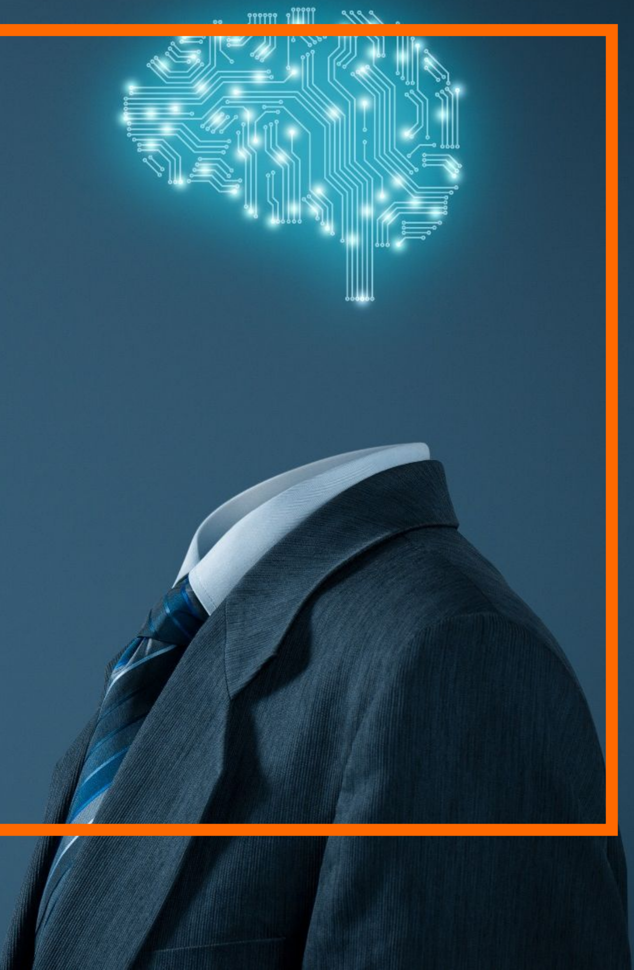
- Growing numbers of contributors
- New features / bug fixes / languages
- Frequent releases

THANK YOU!

Questions?

*(BTW: we're **hiring!**)*

Backup Slides



ZALANDO AT A GLANCE

~4.4 billion EURO
net sales 2017

~214 million visits per month

~24 million active customers

~300,000 product choices

~16,000 employees in Europe

>50% return rate across all categories

>2,000 brands

17 countries

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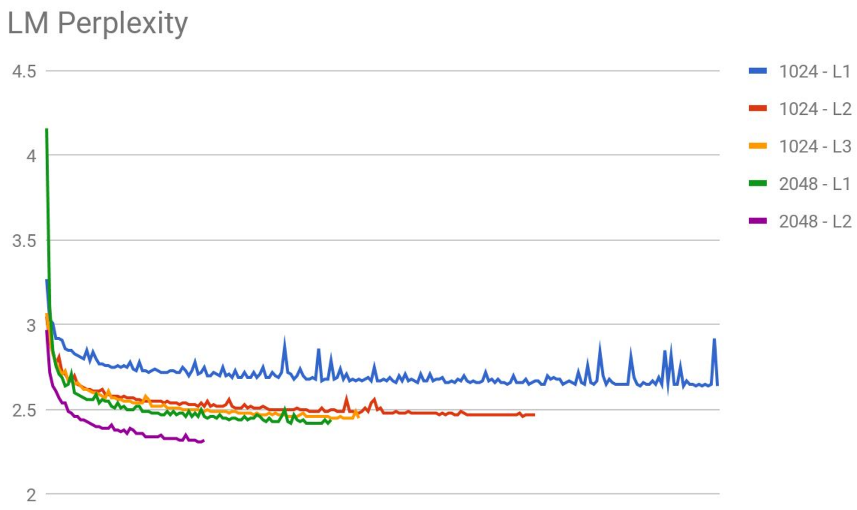
TRAINING CHARACTER LANGUAGE MODELS

Hidden states, layers

- 1 GPU, 1 week

ELMo model:

- 32 GPUs, 5 weeks



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QUALITATIVE INSPECTION

word	context	selected nearest neighbors
Washington	(a) ***Washington*** *to curb support for [..]*	(1) ***Washington*** *would also take [..] action [..]* (2) ***Russia*** *to clamp down on barter deals [..]* (3) ***Brazil*** *to use hovercrafts for [..]*
Washington	(b) *[..] Anthony* ***Washington*** *(U.S.) [..]*	(1) *[..] Carla* ***Sacramento*** *(Portugal) [..]* (2) *[..] Charles* ***Austin*** *(U.S.) [..]* (3) *[..] Steve* ***Backley*** *(Britain) [..]*
Washington	(c) *[..] flown to* ***Washington*** *for [..]*	(1) *[..] while visiting* ***Washington*** *to [..]* (2) *[..] journey to New York City and* ***Washington*** *[..]* (14) *[..] lives in* ***Chicago*** *[..]*
Washington	(d) *[..] when* ***Washington*** *came charging back [..]*	(1) *[..] point for victory when* ***Washington*** *found [..]* (4) *[..] before* ***England*** *struck back with [..]* (6) *[..] before* ***Ethiopia*** *won the spot kick decider [..]*
Washington	(e) *[..] said* ***Washington*** *[..]*	(1) *[..] subdue the never-say-die* ***Washington*** *[..]* (4) *[..] a private school in* ***Washington*** *[..]* (9) *[..] said* ***Florida*** *manager John Boles [..]*

DIRECT PROJECTION

Embedding + Architecture	NER-English F1-score	NER-German F1-score	Chunking F1-score	POS Accuracy
PROPOSED$_{+\text{WORD}}$				
+BiLSTM-CRF	93.07 ± 0.10	88.20 ± 0.21	96.70 ± 0.04	97.82 ± 0.02
+Map-CRF	90.17 ± 0.06	85.17 ± 0.04	96.05 ± 0.04	97.62 ± 0.01
+Map	79.86 ± 0.12	76.97 ± 0.16	90.55 ± 0.05	97.35 ± 0.01
PROPOSED				
+BiLSTM-CRF	91.97 ± 0.04	85.78 ± 0.18	96.68 ± 0.03	97.73 ± 0.02
+Map-CRF	88.62 ± 0.15	82.27 ± 0.22	95.96 ± 0.05	97.53 ± 0.02
+Map	81.42 ± 0.16	73.90 ± 0.09	90.50 ± 0.06	97.26 ± 0.01
CLASSIC WORD EMBEDDINGS				
+BiLSTM-CRF	88.54 ± 0.08	82.32 ± 0.35	95.40 ± 0.08	96.94 ± 0.02
+Map-CRF	66.53 ± 0.03	72.69 ± 0.12	91.26 ± 0.04	94.06 ± 0.02
+Map	48.79 ± 0.27	57.43 ± 0.12	65.01 ± 0.50	89.58 ± 0.02

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