Insights into Subword Embeddings

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A different take on composition

- How to compose words?

A different take on composition

- How to compose words?
- What to compose into words!

Outline

1. Background
   - Word embeddings
   - Embeddings with subwords
2. Hashing trick
3. Explicit ngram lookup
4. Introspection & Evaluation
5. Conclusion & Outlook

Background

Background

Word embeddings

- Word representations in low-dimensional vector space.
- Trained unsupervisedly by predicting word-context co-occurrence.
  1. CBOW - given n context words, predict probability of the focus word
  2. skipgram - given a focus word, predict probability of context words

The skipgram algorithm

Mikolov et al. (2013) - word2vec

Skipgram with negative sampling

They$_c$ made$_c$ **some** tasty$_c$ food$_c$

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- Each context *word*$_c$ is a positive example for **some**
  - $\rightarrow$ For each *word*$_c$, query the model for $p(positive|\textbf{some}, word_c)$
  - $\rightarrow$ Update *word*$_c$ and **some** to increase probability.

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  - → Update *word*$_c$ and **some** to increase probability.
- For each positive, draw n random, negative samples
  - → Query for $p(positive|\textbf{some}, random_c)$
  - → Update embeddings to decrease probability.

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They$_c$ made$_c$ **some** tasty$_c$ food$_c$

- Each context $word_c$ is a positive example for **some**
  - → For each $word_c$, query the model for $p(positive|\textbf{some}, word_c)$
  - → Update $word_c$ and **some** to increase probability.
- For each positive, draw n random, negative samples
  - → Query for $p(positive|\textbf{some}, random_c)$
  - → Update embeddings to decrease probability.
- **word** and $word_c$ are distinct vectors.

Structured Skipgram

Ling et al. (2015)

Structured Skipgram

They_{c-1}	**made**	some_{c+1}	tasty_{c+2}	food_{c+3}
They_{c-2}	made_{c-1}	**some**	tasty_{c+1}	food_{c+2}

- Context words are typed by their offset wrt. the focus word.
- Vectors of context words at different offsets are distinct.
  - → They_{c-1} != They_{c-2}
  - → more focused contexts, sparser updates
- Typically perform better on syntactic tasks

Embeddings with subword information

Bojanowski et al. (2017) - fastText

Embeddings with subword information

$$\begin{array}{ccccc} & & <\text{so}_f + & & \\ & & \text{som}_f + & & \\ & & \text{ome}_f + & & \\ & & \text{me}>_f + & & \\ \text{He}_c & \text{made}_c & \textbf{some}_f & \text{tasty}_c & \text{food}_c \end{array}$$

- Ngrams also have embeddings.
- Words are represented by the average of their ngrams
  - → Ngram embeddings are shared across words.
  - → Orthographically similar words get similar representation.
- Known words get an additional, distinct vector

Structured skipgram with subword information

https://github.com/finalfusion/finalfrontier

Structured skipgram with subword information

$$\begin{array}{ccccc} & & \text{<so} + & & \\ & & \text{som} + & & \\ & & \text{ome} + & & \\ & & \text{me>} + & & \\ \text{He}_{c-2} & \text{made}_{c-1} & \textbf{some} & \text{tasty}_{c+1} & \text{food}_{c+2} \end{array}$$

- Combine structured skipgram with subword information
  → Better embeddings for syntactic tasks and broader coverage.

How are ngrams extracted?

How are ngrams extracted?

- Set a minimum and maximum length
  $\rightarrow$ typically 3 and 6
- Bracket words with '<' and '>'
  $\rightarrow$ with minimum length 3, all words will generate ngrams

How are ngrams extracted?

Word	Ngrams	#
a	<a>	1
is	<is + is>+ <is>	3
and	<an + and + nd> + <and + and>+ <and>	6
some	<so + som + ome + me> + <some + some + ome> + <some>	8

→ Examples of extracted ngrams in range 3-6

How are ngrams extracted?

- At length 4, each additional character adds 4 new ngrams.
  - → *Universitätsstadt* yields 62 distinct ngrams.
  - → *Eberhard-Karls-Universität* generates 98 distinct ngrams.

Isn't that a lot of ngrams?

Given a large corpus, how to accomodate all the in-vocabulary ngrams?

Hashing trick

The hashing trick

Hashing trick

fastText uses the *hashing trick* to bound memory requirements.

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Ingredients:

- Desired number of ngram embeddings
- A fast hashing function: FNV-1a

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Recipe:

- Calculate hash for an ngram.
- Map hash to the ngram embedding space

Hashing trick

Consequences:

- Ngrams don't need to be explicitly stored
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- Number of ngram embeddings is independent of the corpus.

But! the number of ngrams is not independent of corpus size.

$\rightarrow$ Where do the additional ngrams go?

Who is actually tricked?

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Hashing collisions

Collisions

- FNV-1a is not a perfect hashing function.
  - → Hashing collisions happen at random.
  - → Random words share parameters.

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Examples	
Hausfriedens**bruchs**	Friede**nsoppo**sition
Jawohl	Pro**fessor**
Recrui**ting-A**bteilung	P**ickel**hauben-Kompanie

→ Taken from TüBa-D/Z with 2^{21} buckets.

Unknown ngrams

Unknown ngrams

- FNV-1a has an answer for every piece of data
  - $\rightarrow$ Out-of-vocabulary ngrams get mapped to random buckets.

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Known	Unknown
Tsunamei	Multim**ediav**orführungen
B**irthd**ay	H**olzpul**t
N**otst**and	Voka**lakrob**at

→ Taken from TüBa-D/Z with 2^{21} buckets.

The hashing trick in real-life

Data:

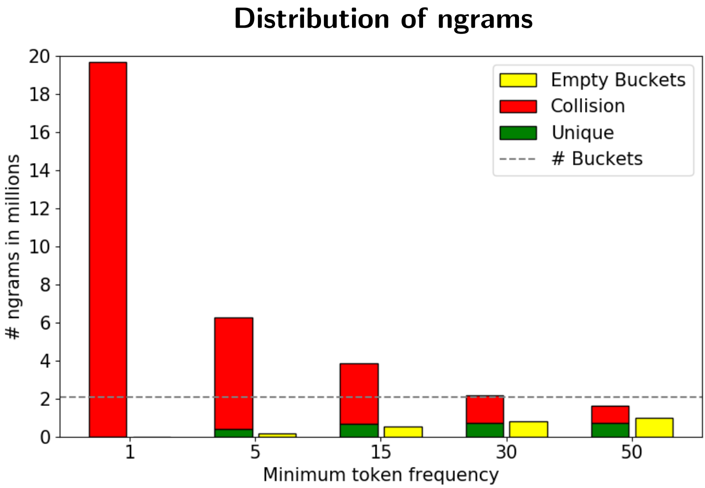
- Non-webcrawled part of TüBa-D/DP corpus (de Kok and Pütz, 2019)
  - $\rightarrow$ **TWE**: **T**AZ[1] + **W**ikipedia[2] + **E**uroparl
  - $\rightarrow$ 1.3 billion tokens, 12.9 million types
  - $\rightarrow$ 19.7 million distinct ngrams
- Only ngrams of in-vocabulary tokens are considered

Parameters:

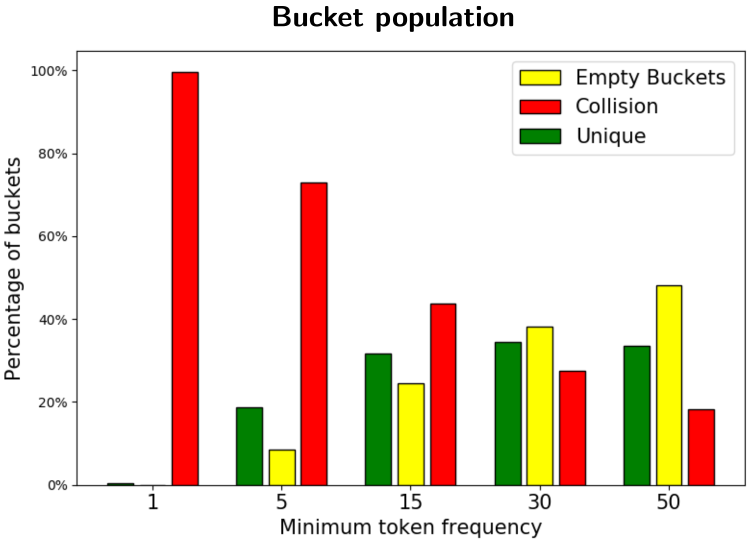
- 2^{21} buckets $\approx$ 2.1 million ngram embeddings
  - $\rightarrow$ closest power of 2 to the default fastText number

[1] 20 years of newspaper text
[2] January '19 dump

Ngram distribution



Bucket population



The hashing trick in words

- For minimum frequency 30:
  - → less than 60000 buckets are missing
  - → 38% are wasted
  - → 27% hold multiple, random ngrams
  - → 35% cleanly map to a single ngram

The hashing trick in words

- For minimum frequency 30:
  - → less than 60000 buckets are missing
  - → 38% are wasted
  - → 27% hold multiple, random ngrams
  - → 35% cleanly map to a single ngram
- TWE has 19.7 million distinct ngrams
  - → Processing the corpus means retrieving an embedding for every ngram
  - → With 2^{21} available buckets, that means more than **9** ngrams per embedding

FNV-1a?

- Is the FNV-1a algorithm just bad at hashing?

FNV-1a?

- Is the FNV-1a algorithm just bad at hashing? **No!**
  - → $\left(\frac{\mathbf{b-1}}{\mathbf{b}}\right)^{\mathbf{n}}$ given *b* buckets and *n* items is the probability of an empty bucket
  - → empirical 38% vs. expected 36%

How does that even work?

- **How does that even work?**

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- **How does that even work?**
  - → Random initialization is near-zero
  - → model has a lot of redundancy.

Do we need the hashing trick?

Do we need the hashing trick to bound memory?

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- On TWE with mininum frequency 30
  - $\rightarrow$ No, the number of ngram embeddings grows by only 2.7%.

Do we need the hashing trick?

Do we need the hashing trick to bound memory?

- On TWE with mininum frequency 30
  - $\rightarrow$ No, the number of ngram embeddings grows by only 2.7%.
- For larger vocabularies
  - $\rightarrow$ Filter ngrams by frequency.
  - $\rightarrow$ Set vocabulary size instead of number of buckets.

Two approaches

Two approaches to explicit storage:

1. After training, build an index with actually trained ngrams.
   - $\rightarrow$ Possibly downsizes the model.
   - $\rightarrow$ No more lies about unknown ngrams.
   - $\rightarrow$ In-vocab collisions remain.

Two approaches

Two approaches to explicit storage:

1. After training, build an index with actually trained ngrams.
   - $\rightarrow$ Possibly downsizes the model.
   - $\rightarrow$ No more lies about unknown ngrams.
   - $\rightarrow$ In-vocab collisions remain.
2. Train embeddings with a proper hash-table.
   - $\rightarrow$ No wasted space, no trade-off between collisions and space.
   - $\rightarrow$ No lies about unknown ngrams.
   - $\rightarrow$ No collisions.

Comparison: Explicit storage vs. Hashing trick

Hyperparamters	
Corpus	TWE
Dimensions	300
Context Window	10
Negative Samples	5
Ngram Range	3-6

All embeddings were trained with finalfrontier[3], using structured skipgram.

[3] https://github.com/finalfusion/finalfrontier

Quick stats

Model	# Embeddings	Size
Buckets 2^{21}	$3.28m$	$3.7GB$
Converted 2^{21}	$2.76m$	$3.2GB$
Explicit	$4.39m$	$5.5GB$
	Mincount 15	

Quick stats

Model	# Embeddings	Size
Buckets 2^{21}	$3.28m$	$3.7GB$
Converted 2^{21}	$2.76m$	$3.2GB$
Explicit	$4.39m$	$5.5GB$
Mincount 15		
Buckets 2^{20}	$1.76m$	$2.0GB$
Converted 2^{20}	$1.59m$	**1.9GB**
Buckets 2^{21}	$2.81m$	$3.2GB$
Converted 2^{21}	$2.01m$	$2.3GB$
Explicit	$2.87m$	$3.3GB$
Mincount 30		

Introspection

Introspection

Introspection

1. How much of the word representation is encoded in ngrams?
2. Do explicit ngram lookups make a difference?

Introspection

- **Known words**: average of ngrams and a distinct word vector
  $\rightarrow$ leave out distinct word vector

Introspection

- **Known words**: average of ngrams and a distinct word vector
  $\rightarrow$ leave out distinct word vector
- Compare known and OOV representation.
- Analyse similarity of known representation with most similar ngram.

Introspection

Model	OOV Sim
Buckets 2^{21}	0.991
Explicit	0.993
Mincount 15	

Introspection

Model	OOV Sim
Buckets 2^{21}	0.991
Explicit	0.993
Mincount 15	
Buckets 2^{20}	0.983
Buckets 2^{21}	0.986
Explicit	0.988
Mincount 30	

Introspection

- Virtually all information of known words is represented by ngram embeddings.
  - $\rightarrow$ Speed-space trade-off by discarding distinct word vectors possible.
    (mincount 15: $-1.1m$, mincount 30: $-0.7m$)
- Slightly more similarity with less collisions.
  - $\rightarrow$ Lower mincount has more collisions, but other interactions are at play.

Introspection

Model	Top Sim
Buckets 2^{21}	0.516
Explicit	0.563
Mincount 15	

Introspection

Model	Top Sim
Buckets 2^{21}	0.516
Explicit	0.563
Mincount 15	
Buckets 2^{20}	0.494
Buckets 2^{21}	0.532
Explicit	0.585
Mincount 30	

$\rightarrow$ Models rely more on single ngrams with clean lookups.

Extrinsic Evaluation

Extrinsic Evaluation

Evaluation

- **Tasks**
  - → Part-of-speech Tagging
  - → Dependency Parsing
- **Data**
  - → TüBa-D/Z r11 (Telljohann et al., 2004)
  - → Random splits: 70% Train, 10% Dev, 20% Val

All models were trained and evaluated with sticker[4].

[4] https://github.com/stickeritis/sticker

Part-of-speech Tagging Setup

Setup

- **Tags:** Concatenation of STTS and UD tags.
  - → Possible to retrieve either tagset by splitting.
  - → Beneficial for dependency parsing as sequence tagging.

Part-of-speech Tagging Setup

Setup

- **Tags:** Concatenation of STTS and UD tags.
  - → Possible to retrieve either tagset by splitting.
  - → Beneficial for dependency parsing as sequence tagging.
- **Model:** 3 stacked Bidirectional LSTMs with 400 hidden units and Residual Connections
- **LR:** 2000 linear warmup steps, followed by plateau scheduler
  - → Stop after 15 epochs without improvement.

Part-of-speech Tagging Results

Model	**Accuracy**
Buckets 2^{21}	99.19
Converted 2^{21}	**99.21**
Explicit	**99.21**
Minimum Count 15	

Part-of-speech Tagging Results

Model	Accuracy
Buckets 2^{21}	99.19
Converted 2^{21}	**99.21**
Explicit	**99.21**
Minimum Count 15	
Buckets 2^{21}	99.18
Converted 2^{21}	99.19
Buckets 2^{20}	99.17
Converted 2^{20}	99.18
Explicit 30	99.19
Explicit 50	99.19
Explicit 125	**99.21**
Minimum Count 30	

Part-of-speech Tagging Results

Discussion:

- Slight advantages for explicit and converted models.
- Much smaller models achieve virtually the same score.
  $\rightarrow$ *Converted* 2^{20} *is only 60% of the size of Buckets* 2^{21}
- Training with bucket embeddings and evaluating with converted embeddings hurts performance.

Dependency Parsing Setup

Setup

- **Tags:** Relative part-of-speech encoding
  - → Part-of-speeches provided through 10-fold jackknifing.
  - → UD version of TüBa-D/Z (Çöltekin et al., 2017)

Dependency Parsing Setup

Setup

- **Tags:** Relative part-of-speech encoding
  - $\rightarrow$ Part-of-speeches provided through 10-fold jackknifing.
  - $\rightarrow$ UD version of TüBa-D/Z (Çöltekin et al., 2017)
- **Model:** 3 stacked Bidirectional LSTMs with 600 hidden units and Residual Connections, input includes POS embeddings.
- **LR:** 2000 linear warmup steps, followed by plateau scheduler
  - $\rightarrow$ Stop after 15 epochs without improvement.

Dependency Parsing Setup

Setup

- **Tags:** Relative part-of-speech encoding
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- **Model:** 3 stacked Bidirectional LSTMs with 600 hidden units and Residual Connections, input includes POS embeddings.
- **LR:** 2000 linear warmup steps, followed by plateau scheduler
  - → Stop after 15 epochs without improvement.
- **Evaluation:** Punctuation is discarded.

Dependency Parsing Results

Model	LAS	UAS
Buckets 2^{21}	93.50	94.89
Converted 2^{21}	93.55	94.91
Explicit	93.48	94.86
Minimum Count 15		

Dependency Parsing Results

Model	LAS	UAS
Buckets 2^{21}	93.50	94.89
Converted 2^{21}	93.55	94.91
Explicit	93.48	94.86
Minimum Count 15		
Buckets 2^{21}	93.42	94.84
Converted 2^{21}	**93.56**	**94.93**
Buckets 2^{20}	93.52	94.92
Converted 2^{20}	93.54	94.91
Explicit 30	93.48	94.86
Explicit 50	**93.56**	94.88
Explicit 125	93.51	94.89
Minimum Count 30		

Dependency Parsing Results

Discussion:

- Converted models beat the corresponding Bucket models.
- 2^{20} buckets performs unexpectedly well: $+0.1$ LAS vs. 2^{21}
- Explicit lookups don't seem to offer improvements.
- No change in accuracy when using converted models to predict.

Conclusion

Conclusion:

- Subword embeddings hold almost the full information.
  - $\rightarrow$ Speed-space tradeoff by discarding word vectors.
- Only small effect on downstream models.
  - $\rightarrow$ Large capacity of the considered models might lower impact of embeddings.
  - $\rightarrow$ More collisions do not hurt performance on the given tasks.
- Converting bucket to explicit models is beneficial.
  - $\rightarrow$ Downsizes the model while improving performance.

Outlook

Outlook:

- Evaluate how explicit lookups interact with pretraining.
- Fine-tune downsized embeddings on downstream tasks.

Thank you

Thank you for your attention!

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Part-of-speech Tagging Results

Model	Accuracy
Buckets 15/21	99.19
Explicit 15/15	**99.21**
Converted 15/21	**99.21**
Buckets 30/21	99.18
Converted 30/21	99.19
Buckets 30/20	99.17
Converted 30/20	99.18
Explicit 30/30	99.19
Expl 30/50	99.19
Expl 30/100	99.14
Expl 30/125	**99.21**

Dependency Parsing Results

Model	**LAS**	**UAS**
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Minimum Count 15		
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Buckets 2^{20}	93.52	94.92
Converted 2^{20}	93.54	94.91
Explicit	93.48	94.86
Minimum Count 30		
Explicit 30/50	**93.56**	94.88
Explicit 30/100	93.52	94.90
Explicit 30/125	93.51	94.89