

Towards Machine Translation of Homer

S. Sklaviadis G. R. Crane

The Qualities of Literary Machine Translation , 2019

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

- Matrix factorization methods
- canonical-GreekLit: Embedded
- Evaluating embedding models
- Digression: fitting GloVe on bitext
- Dimension selection
- Current Approaches

3 NMT

- LSTMs with and without pre-trained embeddings
- Loss plots
- Decoded Iliad

Outline

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

- Matrix factorization methods
- canonical-GreekLit: Embedded
- Evaluating embedding models
- Digression: fitting GloVe on bitext
- Dimension selection
- Current Approaches

3 NMT

- LSTMs with and without pre-trained embeddings
- Loss plots
- Decoded Iliad

NLP in Ancient Greek

Starting with Homer

- c. 100 million surviving words produced over more than 2,000 years (750 BCE-1453 CE)
- The canonical-GreekLit corpus: c. 10,000,000 words (<https://github.com/PerseusDL>)
- Homer's *Iliad* and *Odyssey* are two of the oldest Greek texts: c. 750 BCE
- Homer has been consistently translated from antiquity to the present

Outline

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

- **Matrix factorization methods**
- canonical-GreekLit: Embedded
- Evaluating embedding models
- Digression: fitting GloVe on bitext
- Dimension selection
- Current Approaches

3 NMT

- LSTMs with and without pre-trained embeddings
- Loss plots
- Decoded Iliad

Embeddings for Literary NMT

Matrix factorization methods

- The *Iliad* and *Odyssey* together are about 200,000 words.
- For this experiment we fitted 300 dimensional GloVe vectors.
 - Sampling is not a problem for this corpus size, and skipgram is otherwise equivalent.
- We compare the effect on NMT of 3 static, pretrained embedding models.
 - We vary the size and language of the embedding and use them to filter the input of a minimal LSTM NMT model.

Outline

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

- Matrix factorization methods
- **canonical-GreekLit: Embedded**
- Evaluating embedding models
- Digression: fitting GloVe on bitext
- Dimension selection
- Current Approaches

3 NMT

- LSTMs with and without pre-trained embeddings
- Loss plots
- Decoded Iliad

canonical-GreekLit: Embedded

```
In [24]: 1 model_el.most_similar(positive=['Σωκράτης'], topn=20)
```

```
2019-08-18 10:42:46,714 : INFO : precomputing L2-norms of word weight vectors
```

```
Out[24]: [('Εὐλογημένος', 0.5511736869812012),  
( 'ἔφη', 0.5490833520889282),  
( 'ἔλεγεν', 0.5233275890350342),  
( 'Σωφρονίσκου', 0.5107510089874268),  
( 'Σιμωνίδης', 0.5060718059539795),  
( 'Κάτων', 0.49643081426620483),  
( 'Hamaker', 0.49119776487350464),  
( 'Χαιρεφών.', 0.48857277631759644),  
( 'Πλάτων', 0.4855552017688751),  
( 'εἶπεν', 0.4823710322380066),  
( 'καρπαλίμως', 0.48139774799346924),  
( 'φιλοπτολέμοισιν', 0.46180281043052673),  
( 'Δάμης', 0.460811972618103),  
( 'Γουβάζης', 0.46022942662239075),  
( 'Ξενοφών', 0.45998889207839966),  
( 'Μυρτίλος', 0.4573240578174591),  
( 'ὁ', 0.45698195695877075),  
( 'Καίσαρ', 0.4552561342716217),  
( 'Καλλίας', 0.4546433389186859),  
( 'Ἀθηναίος', 0.4501015543937683)]
```


Outline

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

- Matrix factorization methods
- canonical-GreekLit: Embedded
- **Evaluating embedding models**
- Digression: fitting GloVe on bitext
- Dimension selection
- Current Approaches

3 NMT

- LSTMs with and without pre-trained embeddings
- Loss plots
- Decoded Iliad

Analogy

Analogy

```
1 # "boy" is to "father" as "girl" is to ...?
2 #model.most_similar(['girl', 'father'], ['boy'], topn=3)
3 #[(('mother', 0.61849487), ('wife', 0.57972813), ('daughter', 0.56296098))]
4
5 model_el.most_similar(positive=['θεά', 'άνήρ'], negative=['θεός'], topn=20)
6
7 #γυναικῶν γυναίκας (lemma: γυνή) αὐτῆς αὐτή θεά θεά
8 #ἄναξ ἀνῆρ ἀνῆρ θεός
9 #NB women are referred to only in the plural in all of Iliad and Odyssey
```

2019-08-17 15:40:31,860 : INFO : precomputing L2-norms of word weight vectors

```
[('ἄειρεν', 0.5572900772094727),
 ('ἄλόχοισιν', 0.5487604141235352),
```

Analogy

Analogy

```
1 model_en_glove_vecmap_200.most_similar(positive=['goddess', 'man'], negative=['god'], topn=20)

('old', 0.622481107711792),
('spoke', 0.6113817095756531),
('Telemachus', 0.6093279719352722),
('Penelope', 0.6077815294265747),
('So', 0.6040306091308594),
('saying', 0.6017775535583496),
('woman', 0.5903725624084473),
```

A test from inflectional morphology

Tense stem variants should be more distant than mood variants:

λύω

	PRESENT		FUTURE			AORIST			PERFECT	
	ACTIVE	MID.-PASS.	ACTIVE	MIDDLE	PASSIVE	ACTIVE	MIDDLE	PASSIVE	ACTIVE	MID.-PASS.
PRIMARY INDICATIVE	λύω λύεις λύει λύομεν λύετε λύουσι(ν)	λύομαι λύεῖς/-ῃ λύεται λύομεθα λύεσθε λύονται	λύσω λύσεις λύσει λύσομεν λύετε λύσουσι(ν)	λύσομαι λύσεις/-ῃ λύσεται λύσομεθα λύεσθε λύσονται	λυθήσομαι λυθήσει/-ῃ λυθήσεται λυθήσομεθα λυθήσθε λυθήσονται				λέλυκα λέλυκας λέλυκε λέλυκαμεν λέλυκατε λέλυκασι(ν)	λέλυμαι λέλυσαι λέλυται λέλυκαμεν λέλυκαθε λέλυκασι(ν)
SECONDARY INDICATIVE	ἔλυον ἔλυσες ἔλυε ἔλύομεν ἔλύετε ἔλυσον	ἐλύομην ἐλύσου ἐλύετο ἐλύομεθα ἐλύεσθε ἐλύοντο				ἔλυσα ἔλυσας ἔλυσε ἔλύσαμεν ἔλύσατε ἔλυσαν	ἐλύσαμεν ἐλύσω ἐλύσατο ἐλύσασθε ἐλύσαντο	ἐλύθην ἐλύθης ἐλύθη ἐλύθημεν ἐλύθητε ἐλύθησαν	ἐλέλυκα ἐλελύκης ἐλέλυκε ἐλελύκαμεν ἐλελύκατε ἐλελύκασι(ν)	ἐλελύμην ἐλελύσο ἐλελύτο ἐλελύκαμεθα ἐλελύκαθε ἐλελύκασι(ν)
SUBJUNCTIVE	λύω λύῃς λύῃ λύωμεν λύῃτε λύωσι(ν)	λύωμαι λύῃ λύῃται λύωμεθα λύῃσθε λύωνται				λύω λύῃς λύῃ λύωμεν λύῃσθε λύωσι(ν)	λύωμαι λύῃ λύῃται λύωμεθα λύῃσθε λύωνται	λυθῶ λυθῇς λυθῇ λυθῶμεν λυθῃτε λυθῶσι(ν)	λελύκα λελύκης λελύκε λελύκαμεν λελύκατε λελύκασι(ν)	λελυμένος ὥ etc.
OPTATIVE	λύοιμι λύοις λύοι λύοιμεν λύοιτε λύοιεν	λύοιμι λύοιο λύοιτο λύοιμεθα λύοισθε λύοιεν	λύσοιμι λύσοις λύσοι λύσοιμεν λύσοισθε λύσοιεν	λύσοιμην λύσοιο λύοιτο λύσοιμεθα λύσοισθε λύσοιεν	λυθήσοιμι λυθήσοιο λυθήσοιτο λυθήσοιμεθα λυθήσοισθε λυθήσοιεν	λύσαιμι λύσαις (1) λύσαι (2) λύσαιμεν λύσαιτε λύσαιεν (3)	λύσαιμι λύσαιο λύσαιτο λύσαιμεθα λύσαισθε λύσαιεν	λυθείην λυθείης λυθείη λυθείμεν (4) λυθείτε (4) λυθείεν (4)	λελύκοιμι λελύκοις λελύκοι λελύκοιμεν λελύκοιτε λελύκοιεν	λελυμένος εἶην etc.
IMPERATIVE	λύε λυέτω λύετε λυόντων	λύου λυέσθω λύεσθε λυέσθων				λύσον λυσάτω λύσατε λυσάντων	λύσαιμι λυσάσθω λυσασθε λυσάσθων	λυθήντι λυθήτω λυθήτε λυθέντων	λέλυσο λελύσθω λελύσατε λελύσθων	
PARTICIPLE	λύων, -οντος λύουσα, -ης λύον, -οντος	λυόμενος, -ομένη, -ης λυόμενον	λύων, -οντος λύουσα, -ης λύον, -οντος	λυσόμενος, -ομένη, -ης λυσόμενον	λυθησόμενος, -ομένη, -ης λυθησόμενον	λύσας, -αντος λύσασα, -ης λύσαν, -αντος	λυσάμενος, -ομένη, -ης λυσάμενον	λυθείς, -ένης λυθείσα, -ης λυθέν, -ένης	λελυκώς, -ότος λελυκυία, -ας λελυκός, -ότος	λελυμένος, -ομένη, -οντος
INFINITIVE	λύειν	λύεσθαι	λύσειν	λύσεσθαι	λυθήσεσθαι	λύσαι	λυσάσθαι	λυθῆναι	λελυκέναι	λελυθῆναι

(1) also: λύσεις; (2) also: λύσει; (3) also: λύσειαν; (4) also: λυθήμεν, λυθείτε, λυθείσαν.

Nota Bene: λύσαι (optative), λύσαι infinitive and imperative. Compare: παιδεύσαι (imp.), παιδεύσαι (inf.).

Matrix factorization embeddings

Not there yet...

```
1 model_el.relative_cosine_similarity('ποιεῖν', 'ποιεῖ')
```

0.0713372947758188

- Infinitive vs. 3rd singular present primary indicative
- We can refine these models, however, neural embedding models are taking over quickly

Outline

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

- Matrix factorization methods
- canonical-GreekLit: Embedded
- Evaluating embedding models
- Digression: fitting GloVe on bitext
- Dimension selection
- Current Approaches

3 NMT

- LSTMs with and without pre-trained embeddings
- Loss plots
- Decoded Iliad

Digression: Fitting GloVe on Bitext

A curious bag-of-words result



Αχιλλεύς

label Αχιλλεύς

Search

by

Αχι

label

neighbors

100

distance

COSINE

EUCLIDEAN

Nearest points in the original space:

αἰὺς	0.150
δῖος	0.184
ποδάρκης	0.259
πόδας	0.273
ὑφορβός	0.278
παλινῆθεος	0.306
Ὀδυσσεύς	0.313
πολύτιμος	0.314
Ὀρέστης	0.326
εὐρυπόδης	0.399
Ἑκείνος	0.401
Achilles	0.403
οὐνεκ	0.410
εὐρύς	0.420
μυρμηδόνων	0.421
πολύμητις	0.423
ἐπεγόμενοι	0.428
ἐμμεμῶνες	0.430
ἄνε	0.439
ἔάν	0.444

BOOKMARKS (0)

Outline

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

- Matrix factorization methods
- canonical-GreekLit: Embedded
- Evaluating embedding models
- Digression: fitting GloVe on bitext
- **Dimension selection**
- Current Approaches

3 NMT

- LSTMs with and without pre-trained embeddings
- Loss plots
- Decoded Iliad

Dimension Selection

- Dimensionality of word embeddings has a big impact on their performance.
 - An embedding model with a small dimensionality is typically not expressive enough to capture all possible word relations, whereas one with a very large dimensionality suffers from over-fitting.
- Dimensionality is usually selected either ad hoc or by grid search.
- An empirical approach is to first train many embeddings of different dimensionalities, evaluate them on a functionality test (like word relatedness or word analogy), and pick the one with the best performance.

Dimension Selection

- For embedding algorithms that can be formulated as explicit or implicit matrix factorizations such as the LSA, skip-gram and GloVe, Yin & Shen (2018) propose a rigorous dimensionality selection procedure, by measuring the quality of the trained embeddings through a formal metric.
- Patel & Bhattacharyya (2018) propose lower bounds on the the number of dimensions, based on the number of pairwise equidistant words in the corpus vocabulary (as defined by some distance/similarity metric).
 - They suggest that going below these bounds results in degradation of quality of learned word embeddings.

Outline

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

- Matrix factorization methods
- canonical-GreekLit: Embedded
- Evaluating embedding models
- Digression: fitting GloVe on bitext
- Dimension selection
- Current Approaches

3 NMT

- LSTMs with and without pre-trained embeddings
- Loss plots
- Decoded Iliad

Recent developments in words embeddings include ELMo and BERT.

- In ELMo, each word is assigned a representation which is a function of the entire corpus' sentences.
 - The embeddings are computed from the internal states of a two-layers bidirectional Language Model.
- The relation between these newer Neural Network methods to methods that have been shown to be interpretable in terms of matrix factorization is still being explored.

Outline

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

- Matrix factorization methods
- canonical-GreekLit: Embedded
- Evaluating embedding models
- Digression: fitting GloVe on bitext
- Dimension selection
- Current Approaches

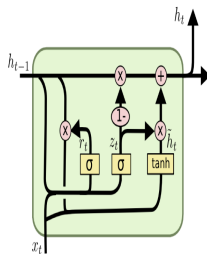
3 NMT

- LSTMs with and without pre-trained embeddings
- Loss plots
- Decoded Iliad

LSTMs with and without Pre-trained Embeddings

Plain LSTM

- Plain LSTM: 7.2
- Homer in Greek: 6.0
- Homer bitext: 6.2
- canonical-GreekLit: 6.4



$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t])$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

2

²OpenNMT, SacreBLEU,

<http://colah.github.io/posts/2015-08-Understanding-LSTMs/>

Outline

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

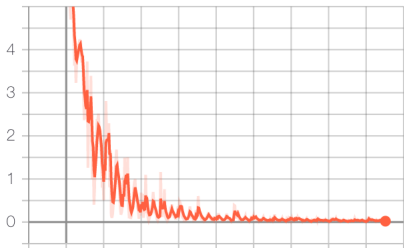
- Matrix factorization methods
- canonical-GreekLit: Embedded
- Evaluating embedding models
- Digression: fitting GloVe on bitext
- Dimension selection
- Current Approaches

3 NMT

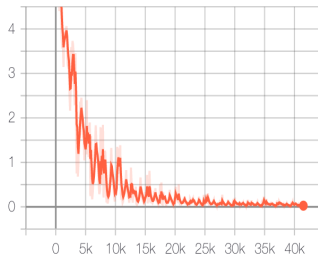
- LSTMs with and without pre-trained embeddings
- **Loss plots**
- Decoded Iliad

Loss Plots

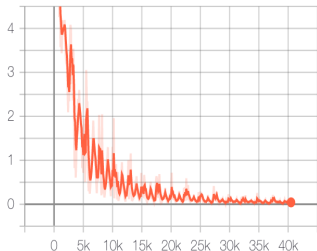
loss



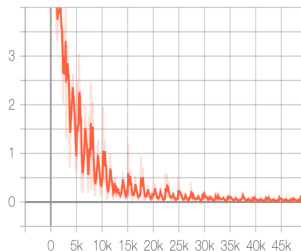
loss



loss



loss



Outline

1 NLP in Ancient Greek

- Introduction to the Corpus

2 Embeddings

- Matrix factorization methods
- canonical-GreekLit: Embedded
- Evaluating embedding models
- Digression: fitting GloVe on bitext
- Dimension selection
- Current Approaches

3 NMT

- LSTMs with and without pre-trained embeddings
- Loss plots
- Decoded Iliad

Decoded Iliad

It almost makes sense!

Plain LSTM

But if thou son of Peleus was first
in the bidding of the first when
thou hast question many horses and
to catch battle if so be he mayest
slay me from the Argives and Ilios
let him fight even from Ilios and
many handmaids layeth goodly
goats and those son of Euaemon
and upsprang Thoas best of the
Achaeans and ever was it to fight
against the gods with a bane What
one came the daughter of Zeus and
said

Butler, 1898

The wrath sing goddess of Peleus'
son Achilles that destructive wrath
which brought countless woes upon
the Achaeans and sent forth to
Hades many valiant souls of heroes
and made them themselves spoil for
dogs and every bird thus the plan
of Zeus came to fulfillment from
the time when first they parted in
strife Atreus' son king of men and
brilliant Achilles Who then of the
gods was it that brought these two
together to contend?