Neural Machine Translation using LSTM with MHA and food-related ontologies

Liviu-Ștefan Neacșu-Miclea – ICA 256/2

The Ontologies

ΑΜΑΛΘΕΙΑ (Amaltheia)

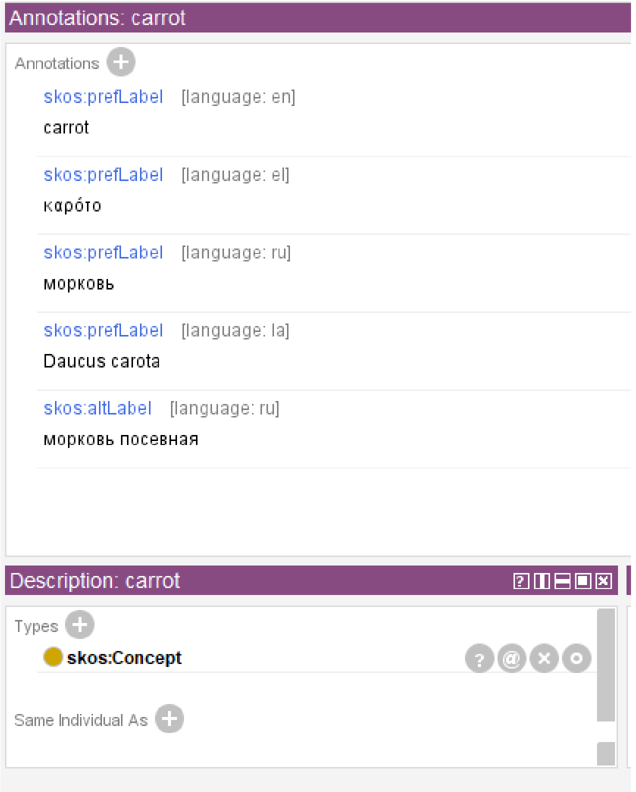
- Has a single Concept class (no hierarchy)
- Has annotated multilingual labels for each individual

FoodOn

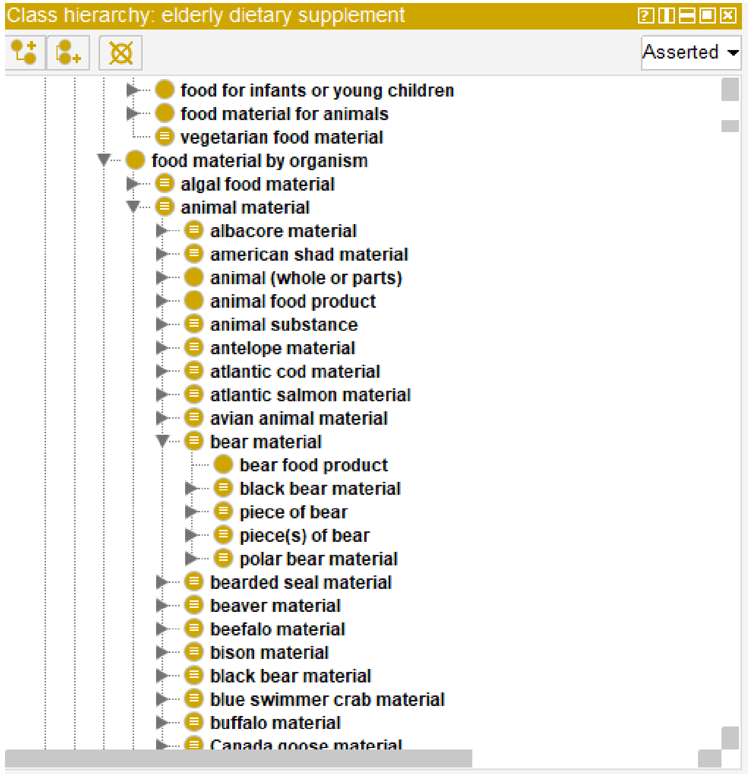
- Has very detailed gastronomical hierarchy
- No multilingual labels
- No individuals except for country names and units of measure

The Ontologies

ΑΜΑΛΘΕΙΑ (Amaltheia)



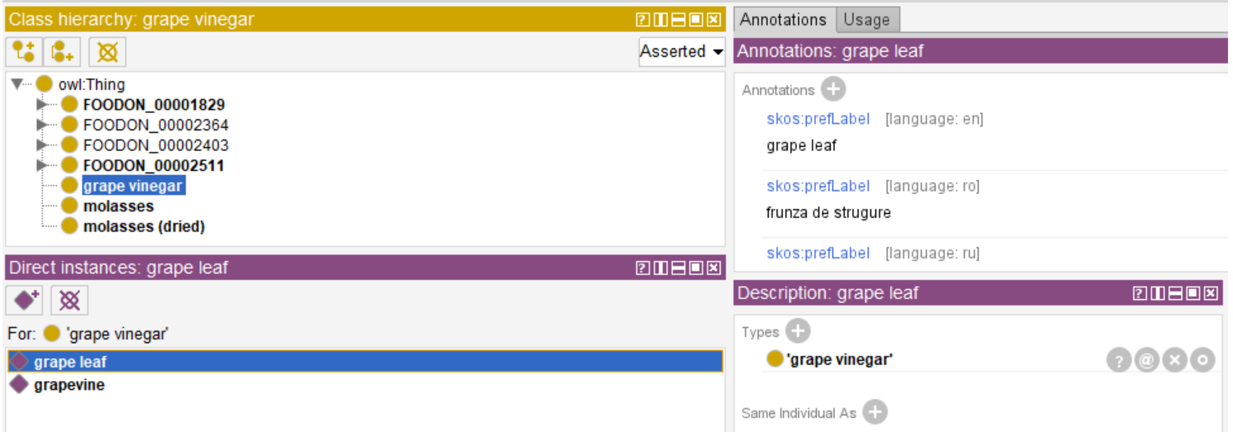
FoodOn



The Ontologies

ΑΜΑΛΘΕΙΑ (Amaltheia) + FoodOn = mini_food_ontology

- I combined (intersected) the two ontologies
- Keep FoodOn's **hierarchy**
- Keep Amaltheia's **multilingual labels**
- Use google translate API to add Romanian translation labels automatically for individual concepts



The Corpus

- OPUS: WikiMatrix.en-ro parallel corpus (opus.nlpl.eu)

1	The first was: "Are there many Jews who think like you?"	Primul a fost: „Sunt mulți evrei care gândesc ca dumneavoastră?”
2	(And I recite to you Allah's statement:) “O People of the Scriptures!	O, oameni ai Cărții!
3	His are the heavens and the earth.	Iată istoria cerurilor și a pământului, când au fost făcute.
4	16 And many of the children of Israel shall he turn to the Lord their God.	El va întoarce pe mulți din fiii lui Israel la Domnul, Dumnezeul lor.
5	How shall I have a son when no man hath touched me?”	Cum să am un copil, când nici un bărbat nu m-a atins?”
6	Anyone who tells you differently is a liar."	Oricine vă spune altfel e un mincinos".
7	In return he would forget Orton ever existed.	În schimb ar uita că Orton a existat vreodată.
8	Q: How can you stop an Albanian tank?	Î: Cum poți opri un tanc albanez?
9	Jack London is not mentioned.	Jack London nu este menționat.
10	Why is there no fish on the market?	De ce nu există pește pe piață?
11	K. visits the lawyer several times.	K. vizitează avocatul de mai multe ori.
12	But Francis and I worked together ...	Însă Francis și cu mine am lucrat împreună ...

Text Preprocessing

Mask foreign characters
Keep latin, Romanian diacritics,
Some common symbols
Mask everything with #

Fit a 1024 wordpieces model
common for both languages

Filter → Cleanup → Annotate → Wordpieces

Remove sentences
Unrelated to ontology
(fuzzy matching)

Fuzzy match ontology
Concepts again and
mark them in-text

Totalling 64084 English-Romanian paired samples

Text Preprocessing

Filtered

Eddy eventually succumbed to his hunger and ate human flesh, but that was soon gone.
Eddy până la urmă a cedat și a mâncat și el carne umană, care curând s-a terminat.

Cleaned

eddy eventually succumbed to his hunger and ate human flesh, but that was soon gone.
eddy până la urmă a cedat și a mâncat și el carne umană, care curând s-a terminat.

Annotated

eddy eventually succumbed to his hunger and ate human [FOODON_33]flesh, but that was soon gone.
eddy până la urmă a cedat și a mâncat și el [FOODON_33]carne umană, care curând s-a terminat.

But...

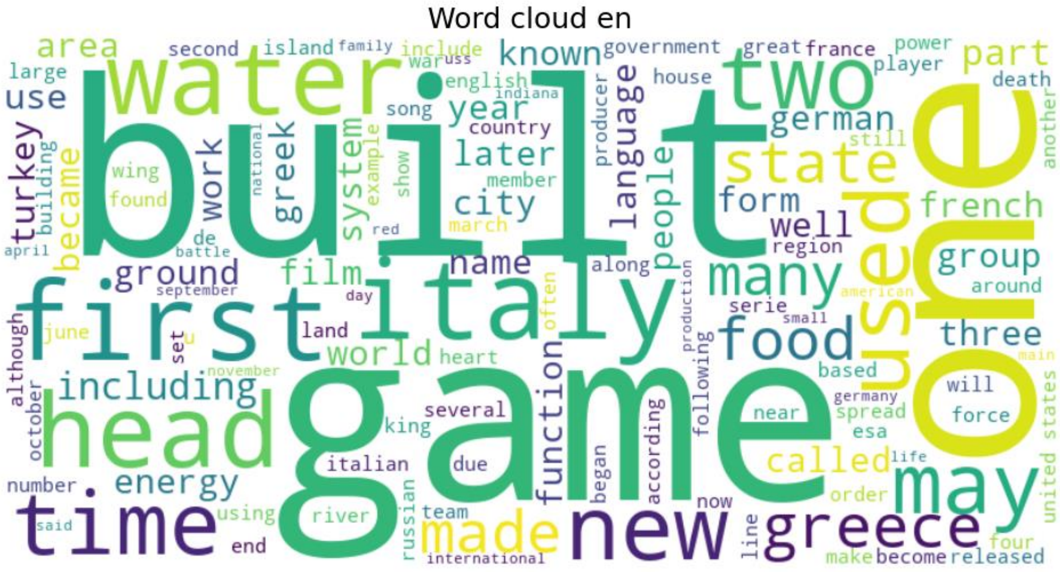
Mismatched translations

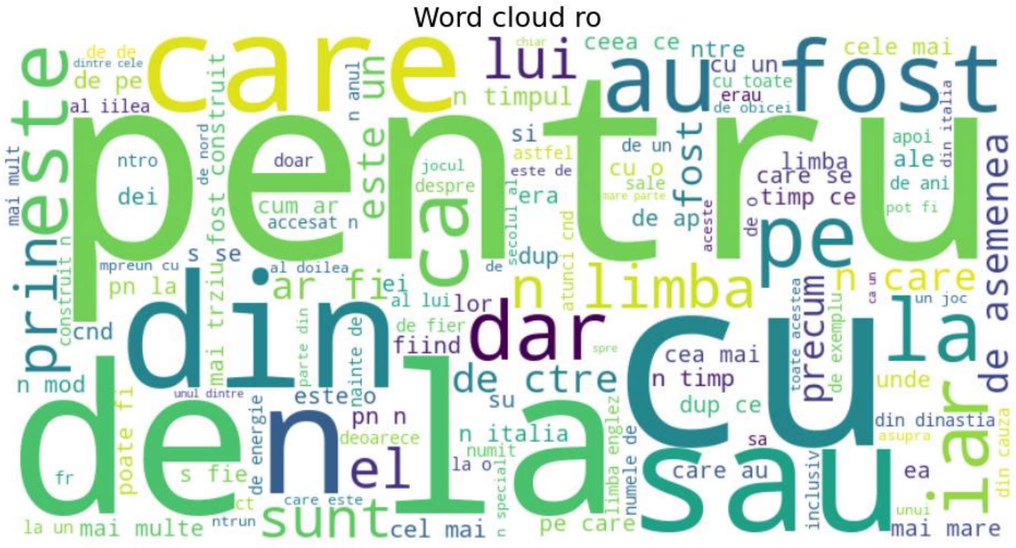
The Italian word frittata derives from friggere and roughly means fried.
cuvântul [FOODON_394]musaca vine din arabă și înseamnă servit rece.

Wrong annotations (Omonyms)

după ce s-a lăsat cortina de [FOODON_1300]fier, ...

Text Preprocessing





Text Preprocessing

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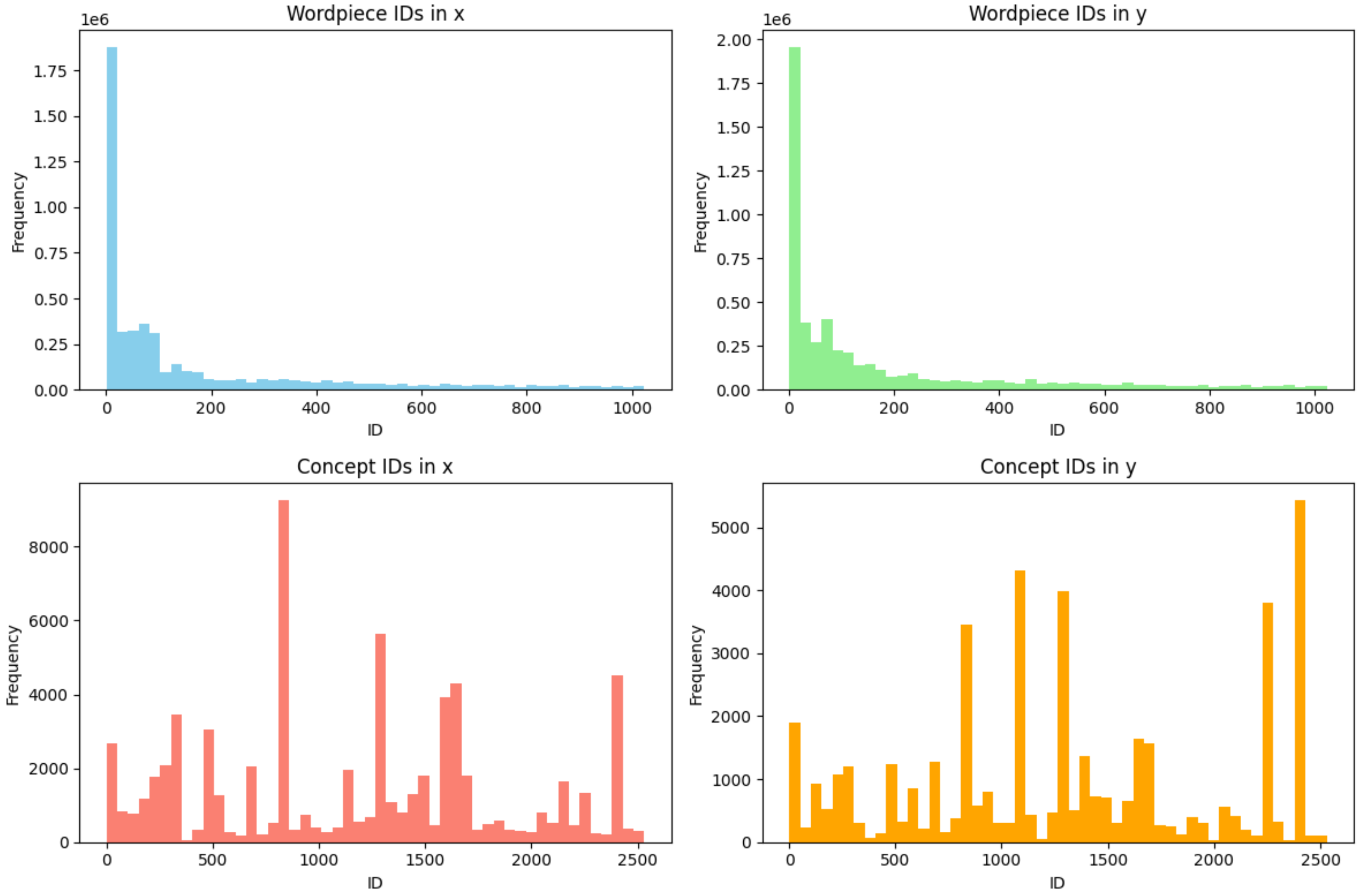
Example wordpieces

Text Preprocessing

- Finally, unique ids were assigned to each individual wordpiece (‘w:<id>’) or concept (‘c:<id>’)

- There were too many concepts in mini food ontology => only the top 128 most frequent were chosen for train

- Max sentence length in ids: 256 (accounts for >95% of all corpus, because of long tail distribution of sentence length)
- Smaller lengths => pad till 256 with w:0 (aka \n)

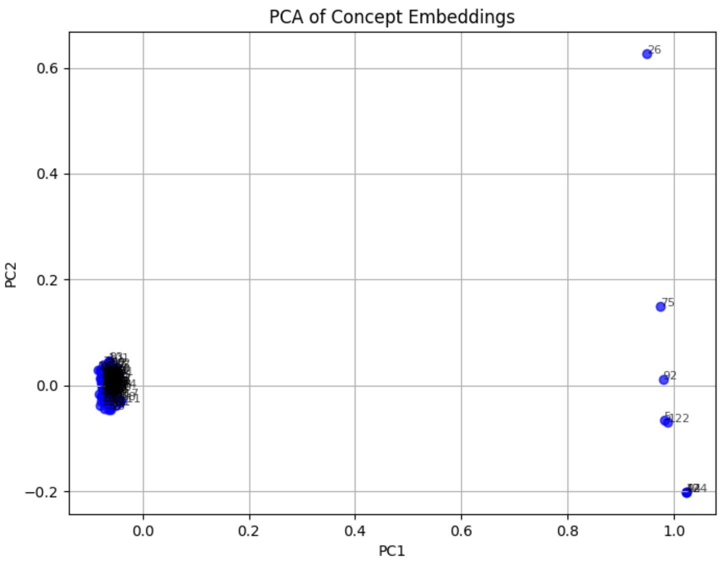


Embeddings

Vectorized tokens, length 127 + 1 dimension for type (-1 concept, 1 wordpiece)

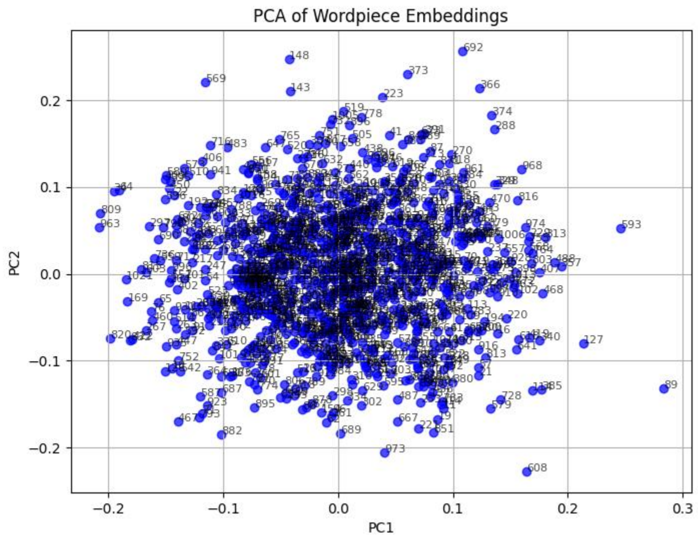
Concept Embeddings

- Poincaré projection computed on hierarchy concept graph
- Hyperbolic to Euclidean conversion



Wordpiece Embeddings

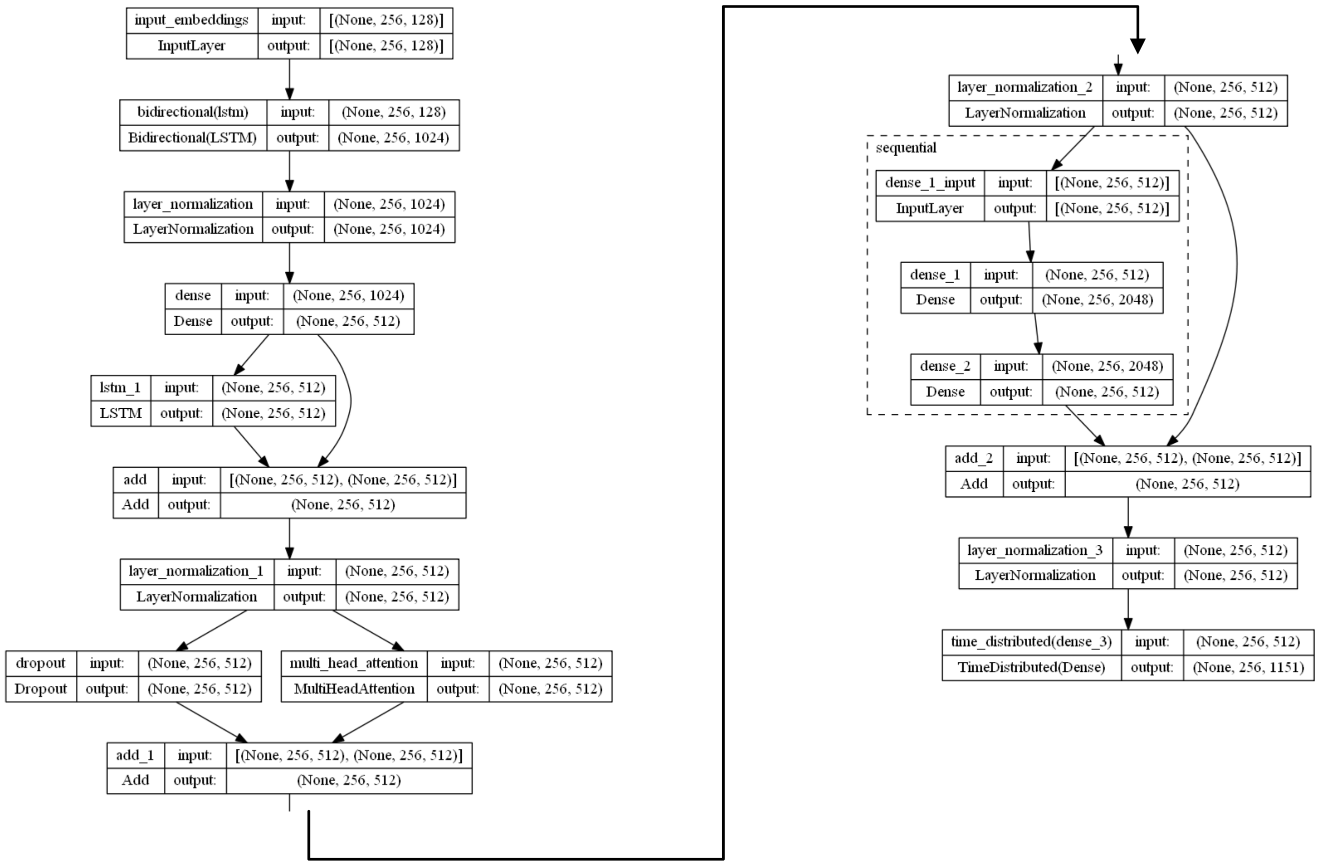
- Randomly chosen from the vector space



NMT Architecture

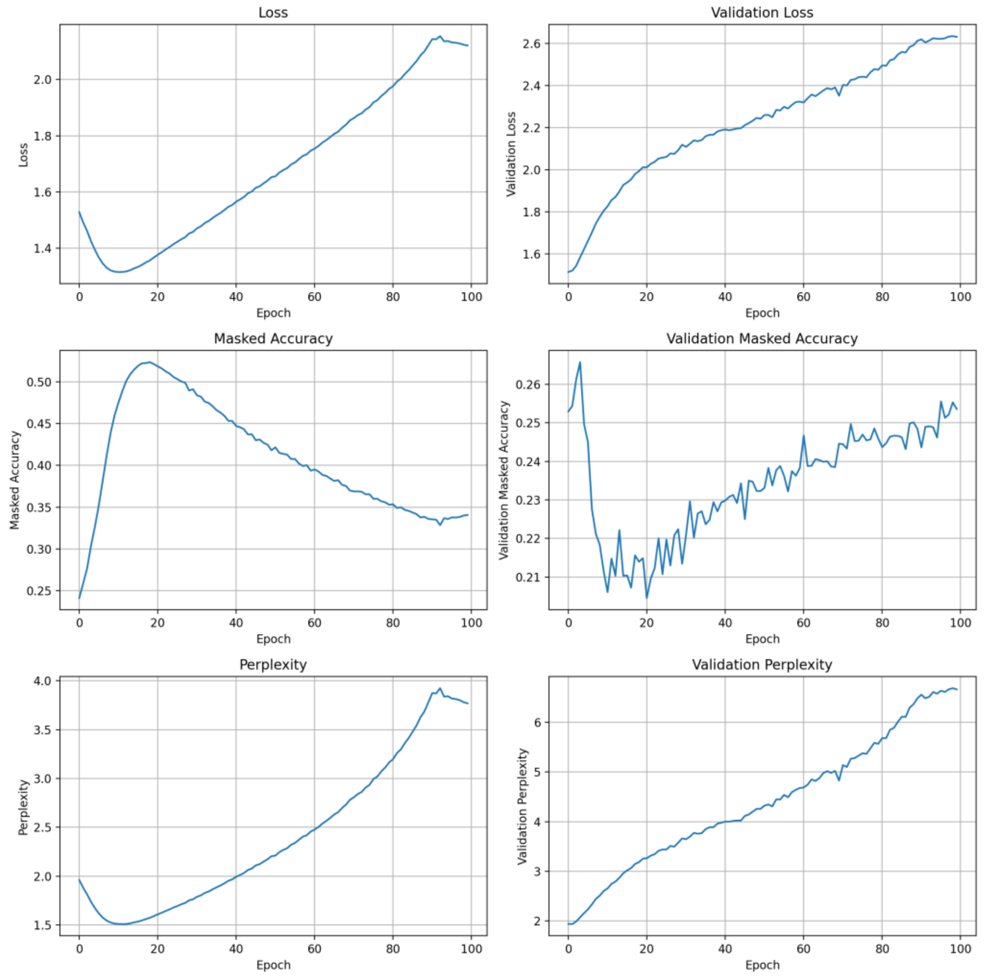
- Bi-LSTM
- LN+Dense
- LSTM+Skip connection
- LN
- MHA
- Fully-Connected
- LN
- Softmax (concepts+wordpieces concatenated categoricals)

- **Curriculum learning**
  - Promote shorter sentences in the early epochs
- Loss = weighted CCE & Focal loss



Experiments

Metric	Value (Val data)
BLEU-4	0.0124
ROUGE-2 ROUGE-L Accuracy	0.0487 0.3298 0.256



Experiments

```
en =  i am eating a delicious [FOODON_939]ice cream.
ro =  ti  tre   o       poant.

en =  the cake contains strawberries.
ro =  aregenareare areun ere   e ați..

en =  it is distinct from the [FOODON_74]mustard plants which belong to the genus brassica.
ro =  se dist men ș plande de șștar carecareapar eeului brassica

en =  saturn is the sixth planet from the sun and the second-largest in the solar system, after jupiter.
ro =  saturn este dea  dinta en   esuleses     li do  mare ile ile ile  l gagaistem

en =  it is used in its [FOODON_872]dried form for japanese soups, tempura, and material for manufacturing [FOODON_872]d
ried nori and tsukudani and [FOODON_1627]rice.
ro =  este folosfolos               ja ja,,        ,                    uu
```

```
[EN] >> I am eating bread.
en =  i am eating [FOODON_93]bread.
ro =  tou suntpapachemâncatineă.
```

Discussion

- Poor performance because
  - The complexity of the task in general

  - Potential noise in data (invalid translations, bad annotations)

  - Unmeaningful embeddings
    - Poincare concept embeddings tend to cluster near a point due to projection of hyperbolic onto Euclidean
    - Wordiece embedding were just randomly chosen

  - Weak architecture (compared to GNMT for example)

Future work

- Carefully clean the train data
- Improve embeddings
  - Try more sparse concept emeddings
  - Word2vec-like on wordpieces
- Improve training pipeline (e.g. losses with length masks & weights)
- Try better architectures

Thank you!