# Working with many languages

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# Outline

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- The good practice is to keep track of the encoding of files, and, as much as possible, use **unicode** encoding (used by default in python 3)
  **NB**: Useful python library for detecting encoding: `chardet`

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- As a consequence of the collaborative nature of the project, Wiktionary is generally deemed to have broad coverage, but unsystematic definitions.

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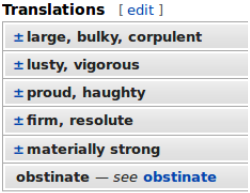

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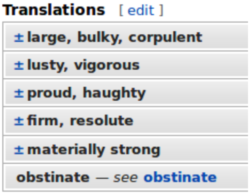


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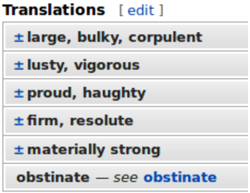


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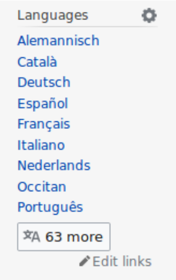
- but it's actually hard work.

- More generally, Wiki-based resources such as Wikipedia, Wiktionary, Wikimedia, etc. often display “interlanguage links” :



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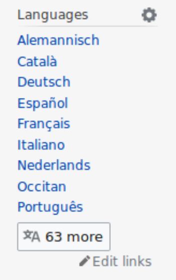


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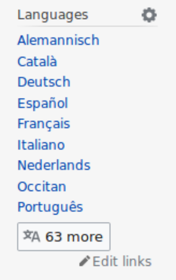


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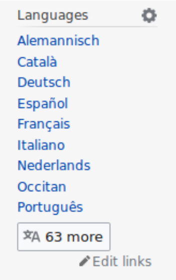


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**NB**: On that note, have a look at the project Omega Wiki: `http://omegawiki.org/`

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- Synsets can be queried with the **`lang`** keyword :

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>>> wn.synsets('cane', lang='ita')
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- The function `wn.all_lemma_names()` can be restricted to a specific language using the `lang` keyword.

1. Write a function that takes a string as a parameter and checks whether it is a valid language code.
2. Write a function that takes a word and a language code as a parameter, and returns all possible translations of this word in that language according to Wordnet.
3. Write a function that takes a word as a parameter, and returns a dictionary mapping all language codes to synsets for this word in the corresponding language.
4. Write a function that takes a language code as a parameter, and returns all synsets that match an existing lemma in this language.
5. Write a function to compute the number and the proportion of synsets that have lemmas in multiple languages

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*There are concerns raised about the quality of Babelnet.*

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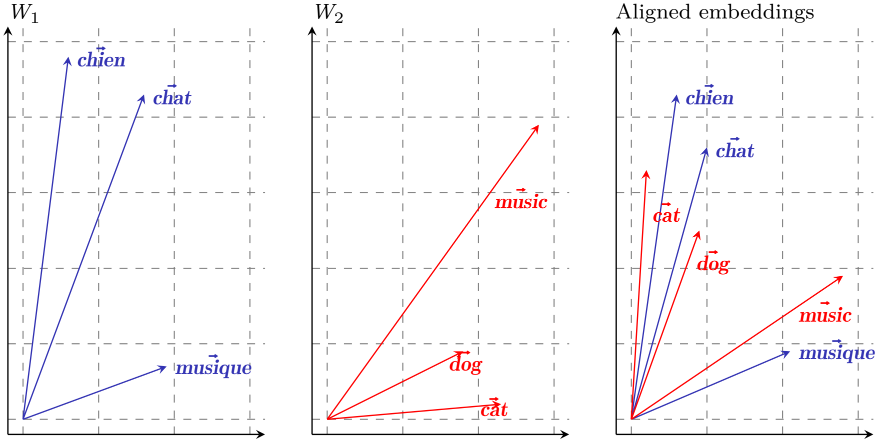

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- The general idea is to learn a linear transformation for vectors from $L_1$ to vectors from $L_2$.

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## Matrix multiplication as a vector function

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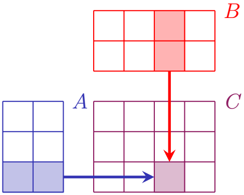

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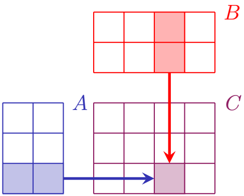
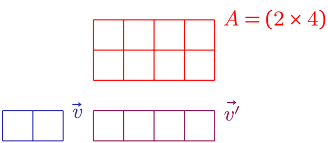



- Therefore the multiplication of a vector $\vec{v}$ of shape $(1 \times d)$ and a matrix $A$ of shape $(d \times d')$ is a vector $\vec{v'} = \vec{v}A$, of shape $(1 \times d')$




- Thus a matrix of shape $(d \times d')$ can be seen as a linear transformation, ie. a function mapping vectors from a space of dimension $d$ to another space of dimension $d'$.

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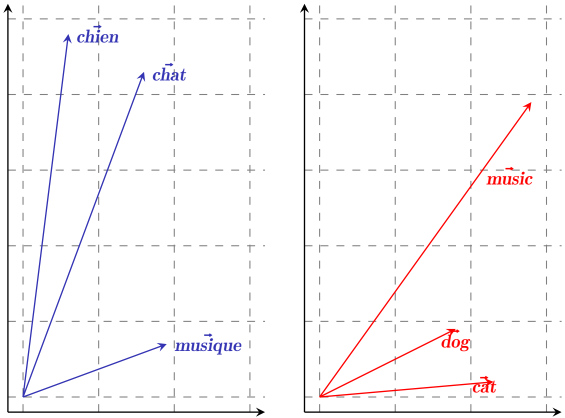


In this example, high values on the $y$ axis in $W_1$ map to low values on the $y'$ axis in $W_2$. This will be captured in the dimension wise-product :

$$P = W_1^T W_2$$

This product defines the conjunction of the distributional descriptions of word vectors : the cell $\langle y, y' \rangle$ corresponding to the importance of $y$ in $W_1$ to compute $y'$ in $W_2$ will be given a low coefficient. Rows in $P$ will correspond to dimensions in $W_1$, and columns to dimensions in $W_2$.

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- $U$ is usually matched to the rows in $M$, and $V$ to the columns in $M$
- in the case of our two semantic spaces $W_1$ and $W_2$, if we define $M$ as the conjunction of the effects in $W_1$ and $W_2$, ie. $M = W_1^T W_2$, we can therefore see $U$ as the rotation mapping $W_1^D$ to its natural description in a shared semantic space, and an approximation of the necessary rotation for $W_1$; likewise, we can see $V$ as a natural description of $W_2$.

In detail, Smith et al. (2017) use the following procedure to align two embedding matrices $W_1$ and $W_2$, using a bilingual lexicon $D = \langle w_1^i, w_2^i \rangle$ :

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# Word-level resources

## Understanding SVD alignment

In detail, Smith et al. (2017) use the following procedure to align two embedding matrices $W_1$ and $W_2$, using a bilingual lexicon $D = \langle w_1^i, w_2^i \rangle$ :

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This is akin to rotating both word embedding spaces so that they are projected in the same space: we use the transformation $U$ on the embedding space $W_1$, the superset of $W_1^D$ as both relates to the rows of the dimension-wise product $P = W_1^{D\,T}\ W_2^D$; likewise we use $V$ on $W_2$. This allows us to mesh together the semantic spaces.

# Exercises I

## Using SVD to align word embeddings, step-by-step

- To align two word embedding spaces, we need to compute for each of them a linear transformation that projects the vectors into a shared space
- Here's a python function that does this :

```
def compute_transformations(WE_fr_paired, WE_en_paired):
    P = WE_fr_paired.T @ WE_en_paired
    u,s,vT = np.linalg.svd(P)
    return u, vT.T
```

- it supposes that `WE_fr_paired` and `WE_en_paired` are two word embeddings matrices where the $i^{\text{th}}$ row in the one corresponds to the translation of the word for the $i^{\text{th}}$ row in the other
- it uses SVD to return two matrices `u` and `vT.T` which are linear transformations and that must be applied to the whole set of vectors (not just the paired ones that were used to compute these transformations)

With that it mind, let's get to it! The following instructions refer to English and French, but feel free to work on any two language you want.

6. write a functions that returns a list of pairs of strings such all of them are a possible translation of the other. Make sure all words are present in the corresponding lookup!

   *You can either use Wordnet, or simply extract strings present in both lookuup dictionaries that match exactly*

# Exercises II

## Using SVD to align word embeddings, step-by-step

7. Download French and English word embedding spaces from fastText: `https://fasttext.cc/docs/en/crawl-vectors.html`.

   **NB**: If your computer doesn't have the resources to handle the full embedding spaces, you can download and use the French and English vector spaces from the github page for this lecture.

8. write a function that takes an embedding matrix, its lookup, and a list of words as parameters, and returns as sub-matrix containing only the rows corresponding to words in the list.

9. Perform the alignment from start to end:
   - 9.1 Using the function written in 6, compute a bilingual lexicon for English and French.
   - 9.2 split this lexicon in a 90/10 ratio; use the list containing 90% of the examples in the remainder of this exercise.
   - 9.3 compute the embedding matrices and the lookup dictionaries for the two vector spaces using the function written in the previous lecture.
   - 9.4 using the function from 8, compute the sub-matrices where the $i^{\text{th}}$ row in the one is the (vectorized) translation of the $i^{\text{th}}$ row of the other.
   - 9.5 compute the transformations. You can use the above `compute_transformations()`.
   - 9.6 apply each transformation to the corresponding whole word vector space (simply use `numpy.matmul` or its alias `@`).

10. using the remaining 10% bilingual examples that were set aside in 9.2, compute
    - 10.1 the average of the cosines of the French word vectors and their English counterparts before applying the transformations
    - 10.2 the average of the cosines of the (transformed) French word vectors and their (transformed) English counterparts after applying the transformations

# Exercises III

Using SVD to align word embeddings, step-by-step

11. what can you conclude from your results on this held out test set?
12. Adapt the function to retrieve the $k$ top candidates written in the previous lecture, so as to retrieve the $k$ most plausible translations for a given word.
13. Rewrite the function in exercise 6 so that it only contains monosemous lemmas. Do you get different results?
14. Try another algorithm! Can you rewrite the alignment function so that it uses a Stochastic Gradient Descent with Mean Squared Error loss? Do you get better results?

# Outline

# Sentence-level resources

## Parallel corpora

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**NB**: you can even find English-Inuktitut parliamentary parallel data : `http://www.inuktitutcomputing.ca/NunavutHansard/info.php`

What does a parallel corpus look like?

What does a parallel corpus look like? Europarl En $\leftrightarrow$ De

| **Source** `europarl-v7.de-en.en` | **Target** `europarl-v7.de-en.de` |
|---|---|
| `1 Resumption of the session` | `1 Wiederaufnahme der Sitzungsperiode` |
| `2 I declare resumed the session of the European Parliament adjourned on Friday 17 December 1999, and I would like once again to wish you a happy new year in the hope that you enjoyed a pleasant festive period.` | `2 Ich erkläre die am Freitag, dem 17. Dezember unterbrochene Sitzungsperiode des Europäischen Parlaments für wiederaufgenommen, wünsche Ihnen nochmals alles Gute zum Jahreswechsel und hoffe, da Sie schöne Ferien hatten.` |
| `3 Although, as you will have seen, the dreaded ...` | `3 Wie Sie feststellen konnten, ist der gefürchtete ...` |

# Sentence-level resources

## Universal annotations

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- Likewise, efforts have been made to consistently annotate morphosyntactical features across languages (for instance Interset by Zeman (2008) has been used to map features across languages, by deriving an "interlingua" representation)

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- Lastly, much research has been made to present a cross-lingual dependency annotation scheme, called "**Universal Dependencies**" (UD, cf. `http://universaldependencies.org`).

# Sentence-level resources

## Universal Dependencies

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- the main idea of the UD project is to be both accessible to the non-specialist (learner, human annotator or NLP engineer) and linguistically accurate for each language (despite being universal).
- the corpora are each split in three (train, dev and test), and are available both as raw `.txt` format and as `.conllu` format

# Sentence-level resources

## `.conllu` format

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    1. **ID**: its index in the sentence
    2. **FORM**: its word form
    3. **LEMMA**: its lemma, if available
    4. **UPOS**: its universal PoS tag
    5. **XPOS**: its language-specific PoS tag
    6. **FEATS**: its morphosyntactic features
    7. **HEAD**: the index of its head, or 0 if it is the root
    8. **DEPREL**: the dependency relation that it holds with respect to its head
    9. **DEPS**: an enhanced graph annotation
    10. **MISC**: any remaining miscellaneous annotation

    Any unspecified or missing information is represented using the _ character. ID cannot be missing. In UD tree banks, the UPOS, HEAD and DEPREL columns must not be unspecified or missing.

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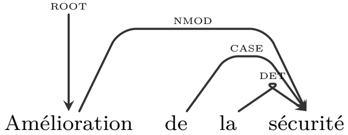
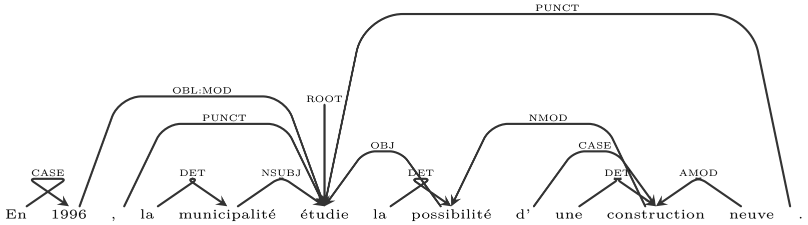
- blank lines separate sentences

# Sentence-level resources
## UD example I




```
# sent_id = annodis.er_00007
# text = Amélioration de la sécurité
1       Amélioration    amélioration    NOUN    _       Gender=Fem|Number=Sing  0       root    _       _
2       de      de      ADP     _       _       4       case    _       _
3       la      le      DET     _       Definite=Def|Gender=Fem|Number=Sing|Pron    Type=Art        4       det     _       _
4       sécurité        sécurité        NOUN    _       Gender=Fem|Number=Sing  1       nmod    _       _
```

# Sentence-level resources




```
# sent_id = annodis.er_00029
# text = En 1996, la municipalité étudie la possibilité d'une construction neuve.
1	En	en	ADP	_	_	2	case	_	_
2	1996	1996	NUM	_	NumType=Card	6	obl:mod	_	SpaceAfter=No
3	,	,	PUNCT	_	_	6	punct	_	_
4	la	le	DET	_	Definite=Def|Gender=Fem|Number=Sing|PronType=Art	5	det	_	_
5	municipalité	municipalité	NOUN	_	Gender=Fem|Number=Sing	6	nsubj	_	_
6	étudie	étudier	VERB	_	Mood=Ind|Number=Sing|Person=3|Tense=Pres|VerbForm=Fin	0	root	_	_
7	la	le	DET	_	Definite=Def|Gender=Fem|Number=Sing|PronType=Art	8	det	_	_
8	possibilité	possibilité	NOUN	_	Gender=Fem|Number=Sing	6	obj	_	_
9	d'	de	ADP	_	_	11	case	_	SpaceAfter=No
10	une	un	DET	_	Definite=Ind|Gender=Fem|Number=Sing|PronType=Art	11	det	_	_
11	construction	construction	NOUN	_	Gender=Fem|Number=Sing	8	nmod	_	_
12	neuve	neuf	ADJ	_	Gender=Fem|Number=Sing	11	amod	_	SpaceAfter=No
13	.	.	PUNCT	_	_	6	punct	_	_
```

# Exercises I

## Universal dependency

15. Retrieve and unzip the Sequoïa UD-treebank corpus available on the github for this lecture.
16. write a function that turns the string for a token into the list of its fields
17. write a function that turns the string of a well-formed sentence into a list of parsed tokens
18. write a function that read a `.conllu` file and returns a list of parsed sentences
19. Test your code: open the train file for the sequoïa corpus. How many sentences are there? how many tokens?
20. write a function that takes the path of a UD tree bank, and returns a list of all the parsed sentences where the root is not a verb. Test it on UD tree banks for different languages. What different results do you get?
21. write a function that takes the path of a UD tree bank, and a token-level query, and returns all the sentences that match this query. The query can be represented as a list of length 10, where each element is the value required for the corresponding column of the token, or `None` if no value is required for that column.
22. write a function that takes the path of a UD tree bank, creates a SQL database and populates it accordingly. Your SQL schema should at least contain tables for sentences, tokens and features (FEATS column of the tokens). Try to conserve all the meta-annotations (starting with #) for sentences as well. Try writing a SQL query to retrieve sentences where the root is not a verb.

# Outline

# Detecting Language

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  - Other issues include cross-language homographs : compare French and English “pour”.
- Documents in different languages do not “look the same”. We can classify documents according to their language based on “how they look”.
  - We can look at the distribution of their words : a document containing the word “the” is likely to be in English
  - We can look at the distribution of their characters : a document containing the sequence “kno” is most likely not in French. The distribution of characters is actually specific to each language.

# Exercise I

## Detecting Language using character n-grams, step-by-step

23. write a function that takes a word as parameters and returns the list of **trigrams** it contains : eg. the word “banana” should return the list `['##b', '#ba', 'ban', 'ana', 'nan', 'ana', 'na#', 'a##']`
    As a variation you can also modify this function by adding a parameter $n$ and returning the n-grams for the word.
24. write a function that takes a sentence as a parameter, that computes trigrams for each word in it and returns a dictionary that maps trigrams to their number of occurrences in the text: eg. the sentence “i like ike” should return the dictionary `{"##i" : 2, "#i#" : 1, "i##" : 1, "##l" : 1, "#li" : 1, "lik" : 1, "ike" : 2, "ke#" : 2, "e##" : 2, "#ik" : 1}`
    Use the word tokenizer from nltk to split the sentence into words : download the punkt package and import the function word_tokenize from the module nltk.tokenize.
25. write a functions that takes two dictionaries $d_1$ and $d_2$, mapping trigrams to counts, and returns a dictionary mapping trigrams to the sum of their counts in $d_1$ and $d_2$.
26. write a function that receives a list of sentences paired to their language, and returns a dictionary mapping each language to a trigram count based on the relevant sentences.
27. compute the probability distribution of trigrams stored in a dictionary by normalizing their counts : $P(\mathrm{tri}_t, \mathrm{lang}_L) = \frac{\#\mathrm{tri}_t \wedge \mathrm{lang}_L}{\sum_{\mathrm{tri}_{t'}} \#\mathrm{tri}_{t'} \wedge \mathrm{lang}_L}$

# Exercise II

## Detecting Language using character n-grams, step-by-step

28. write a function that computes the **statistical divergence** between two probabilities of tri-grams using the **total variation distance** :

$$\mathrm{tvd}(P,Q) = \frac{1}{2} \sum_{\mathrm{tri}_t} |P(\mathrm{tri}_t) - Q(\mathrm{tri}_t)|$$

29. write a function that receives a text and a dictionary mapping languages to trigram probability distributions, and returns the language that is the most likely for the text (ie. the language for which the tvd yields the lowest value)
30. Test your code!
    - 30.1 Retrieve a few books in a few different languages from the Gutenberg project : `http://www.gutenberg.org/wiki/Category:Bookshelf`
    - 30.2 For each language, write a function to retrieve test from the books, split the texts into sentences and reserve 1 out of every 10 sentences for testing.
    - 30.3 use the remainder 9 out 10 sentences for computing a distribution probability for each language.
    - 30.4 compute **precision** and **recall** for each language over the 10% sentences that were set aside for testing:

$$\mathrm{precision} = \frac{\#\text{True positives}}{\#\text{True positives} + \#\text{False positives}}$$

$$\mathrm{recall} = \frac{\#\text{True positives}}{\#\text{True positives} + \#\text{False negatives}}$$

- true positives for language $L$ are the sentences that are written in $L$ and predicted as such,
- false positives are sentences predicted to be written in $L$ although they aren't,
- false negatives are sentences not predicted to be written in $L$ although they are.

# Exercise III

Detecting Language using character n-grams, step-by-step

31. Does word frequency matter? Modify your code so that the trigrams of a word are only evaluated once for a language. Do you get different results?
32. Other than using statistical divergence, you can try training a simple SVM classifier using probability distributions over trigrams as feature vectors.
33. Rather than using basic count-based probabilities, try to use smoothing. You can use Laplace smoothing :

$$\hat{P}(\mathrm{tri}_t, \mathrm{lang}_L) = \frac{1 + (\#\mathrm{tri}_t \wedge \mathrm{lang}_L)}{\#\mathrm{tri} + \sum_{\mathrm{tri}_{t'}} \#\mathrm{tri}_{t'} \wedge \mathrm{lang}_L}$$