Refining Character Relationships using Embeddings of Textual Units

With case studies on *Les Misérables*

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Introduction

The construction of a character network

The construction of a character network takes generally 3 steps [Labatut and Bost, 2019]:

- Identification of characters.
- Detection of interactions.
- Construction of the graph.

The construction of a character network

When dealing with text, a frequently used method is to count character co-occurrences in predefined textual units (see, e.g., [Elsner, 2012, Rochat and Kaplan, 2014]).

⋮

… cet affaiblissement de la maladie qui ressemble à l'enfance, afin que, la voyant si paisible, on ne fît pas difficulté de lui amener Cosette. Cependant, tout en se contenant, elle ne pouvait s'empêcher d'adresser à M. Madeleine mille questions

⋮

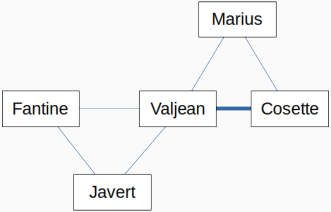
Lorsque Jean Valjean, dans la nuit même du jour où Javert l'arrêta près du lit de mort de Fantine, s'échappa de la prison municipale de Montreuil-sur-Mer,...

⋮

Cosette, un peu moins rêveuse que Marius, était gaie, et cela suffisait à Jean Valjean pour être heureux. Les pensées que Cosette avait, ses préoccupations tendres, l'image de Marius qui lui remplissait l'âme,...

⋮

Character 1	Character 2	Co-occurrences
Cosette	Marius	1
Cosette	Valjean	2
Fantine	Javert	1
Fantine	Valjean	1
Javert	Valjean	1
Marius	Valjean	1



Dataset

In this context, the dataset used to construct the character network has the following form

tome	chapitre	livre	text	Azelma	Babet	Bahorel	Bamatabois	Baptistine	Basque	...	Montparnasse	Myriel	Nicolette	Pontmercy	Prouvaire	Simplice	Tholomyès	Toussaint	Valjean	Zéphine
1	1	1	Monsieur Myriel	0	0	0	0	0	0	...	0	1	0	0	0	0	0	0	0	0
1	1	1	En 1815, M. Charles-François-Bienvenu Myriel était évêque de Digne.	0	0	0	0	0	0	...	0	1	0	0	0	0	0	0	0	0
1	1	1	Quoique ce détail ne touche en aucune manière au fond même de ce que	0	0	0	0	0	0	...	0	4	0	0	0	0	0	0	0	0
1	1	1	En 1804, M. Myriel était curé de Brignolles. Il était déjà vieux, et	0	0	0	0	0	0	...	0	1	0	0	0	0	0	0	0	0
1	1	1	Vers l'époque du couronnement, une petite affaire de sa cure, on ne sait	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	1	1	--Quel est ce bonhomme qui me regarde?	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	1	1	--Sire, dit M. Myriel, vous regardez un bonhomme, et moi je regarde un	0	0	0	0	0	0	...	0	1	0	0	0	0	0	0	0	0
1	1	1	L'empereur, le soir même, demanda au cardinal le nom de ce curé, et	0	0	0	0	0	0	...	0	1	0	0	0	0	0	0	0	0
1	1	1	Qu'y avait-il de vrai, du reste, dans les récits qu'on faisait sur la	0	0	0	0	0	0	...	0	2	0	0	0	0	0	0	0	0
1	1	1	M. Myriel devait subir le sort de tout nouveau venu dans une petite	0	0	0	0	0	0	...	0	1	0	0	0	0	0	0	0	0
1	1	1	Quoi qu'il en fût, après neuf ans d'épiscopat et de résidence à Digne,	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	1	1	M. Myriel était arrivé à Digne accompagné d'une vieille fille,	0	0	0	0	1	0	...	0	1	0	0	0	0	0	0	0	0
1	1	1	Ils avaient pour tout domestique une servante du même âge que	0	0	0	0	1	0	...	0	0	0	0	0	0	0	0	0	0
1	1	1	Mademoiselle Baptistine était une personne longue, pâle, mince, douce;	0	0	0	0	1	0	...	0	0	0	0	0	0	0	0	0	0
1	1	1	Madame Magloire était une petite vieille, blanche, grasse, replète,	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	1	1	À son arrivée, on installa M. Myriel en son palais épiscopal avec les	0	0	0	0	0	0	...	0	1	0	0	0	0	0	0	0	0

However, apart from a few exceptions [Nalisnick and Baird, 2013, Trovati and Brady, 2014, Min and Park, 2019], the content of the text column is not used. Edges in the resulting graph aggregate blindly various kind of interactions.

Approaches

In this presentation, we propose to refine character relationships by using the textual data. Quantities of approaches can be undertaken, but we focus on:

- Bag-of-paths approaches, a corpus is represented by an unit-term matrix.

	abaisser	abandonner	abbé	abominable	aboutir	absence	absolu	absolument	absorber	abîme	accablement	accabler	accent
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	2	0	0	0	1	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	1	1	1	0	2	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	4	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	1	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	1	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	1	0	0	0	3

- Embeddings of textual units. The unit-term matrix is used to construct vectors representing units.
- Embeddings of characters and relationships, which derive from unit vectors.

Approaches

More specifically, three types embeddings are studied:

- Correspondence Analysis (CA) (main work).
- Pre-trained word embeddings (WE) (work in progress).
- "Topical" vectors build from Non-negative Matrix Factorization (NMF) (work in progress).

There also is two methods for constructing character/relationship vectors:

- Centroids.
- Regression coefficients.

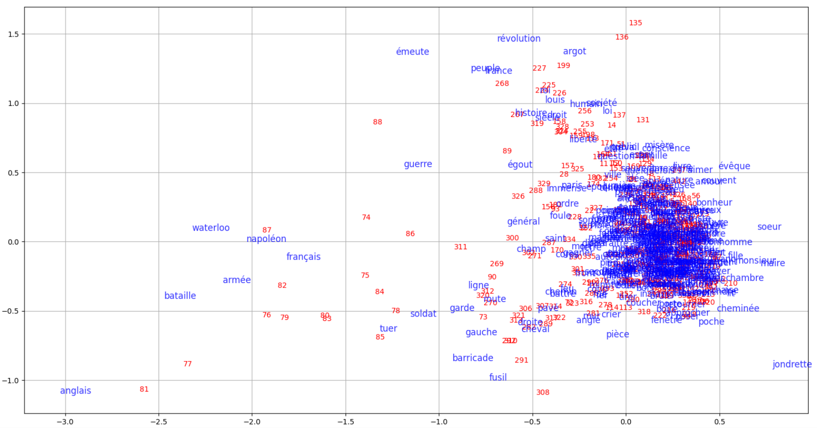
Correspondence Analysis - Centroids

Principles

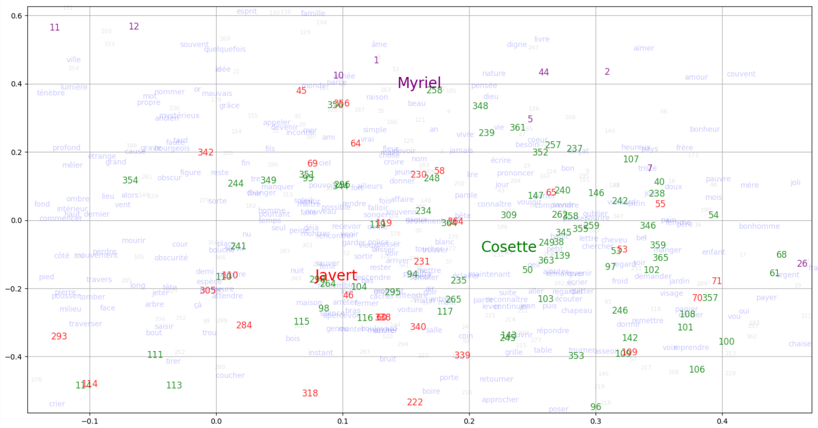
Correspondence Analysis is the natural tool for analyzing textual resources if data is organized in a $(n \times p)$ document-term matrix [Lebart et al., 2019] (here, documents are our textual units). It gives:

- $\min(n, p) - 1$ factorial axes, by decreasing order of importance, which can be interpreted as latent variables.
- Coordinates of each document along these factors, where proximity can be interpreted as similarity in word distributions.
- Coordinates of each word along the same factors, where proximity can be interpreted as similarity in document distributions.
- Affinities between documents and terms, which are computed by the scalar product.

If we plot units and words on the first two axes, we get the usual biplot:



The textual units have natural embedding in CA. For characters, the most intuitive idea is to compute them as centroids of units where they appear.

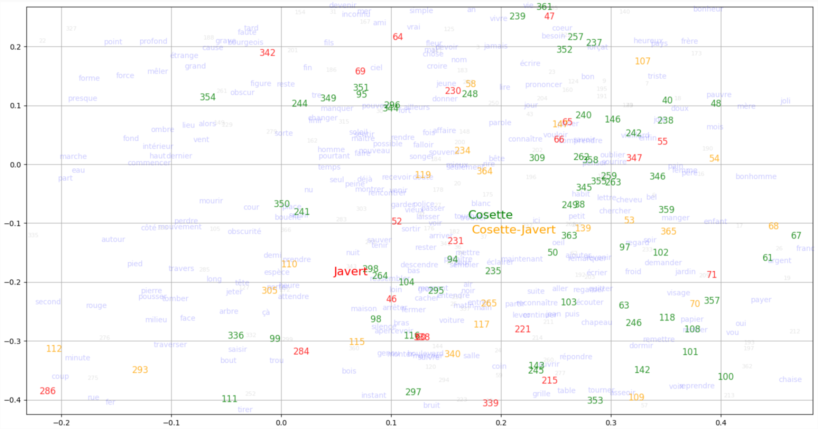


Relationship embeddings - centroids

The same idea can be applied to relationships, In fact, in our dataset, we can extend our table to include interactions (up to a certain order).

chapitre	...	Baptistine	Basque	...	Gillenormand	Grantaire	Gueulemer	...	Montparnasse	Myriel	...	Baptistine-Grantaire	Baptistine-Myriel	Grantaire-Myriel	...	Baptistine-Grantaire-Myriel
1	...	1	0	...	0	0	0	...	0	1	...	0	1	0	...	0
2	...	1	0	...	0	1	0	...	0	1	...	1	1	1	...	1
3	...	0	0	...	0	0	0	...	0	0	...	0	0	0	...	0
4	...	0	0	...	0	1	0	...	0	1	...	0	0	1	...	0
5	...	1	0	...	0	1	0	...	0	1	...	1	1	1	...	1
6	...	1	0	...	0	0	0	...	0	1	...	0	1	0	...	0
7	...	1	0	...	0	0	0	...	0	1	...	0	1	0	...	0
8	...	0	0	...	0	0	0	...	0	1	...	0	0	0	...	0
9	...	1	0	...	0	1	0	...	0	0	...	1	0	0	...	0
10	...	0	0	...	0	1	0	...	0	1	...	0	0	1	...	0
11	...	1	0	...	0	1	0	...	0	1	...	1	1	1	...	1
12	...	0	0	...	0	1	0	...	0	1	...	0	0	1	...	0
13	...	0	0	...	0	0	0	...	0	1	...	0	0	0	...	0
14	...	0	0	...	0	0	0	...	0	1	...	0	0	0	...	0
15	...	0	0	...	0	1	0	...	0	0	...	0	0	0	...	0

This leads us with embeddings of relationships:



Character/relationship embeddings - usages

What can we do with these character/relationship embeddings ?

As they are in the same space as textual units, we can:

- Get the Euclidean distance between relationships.
- Get the Euclidean distance between relationships and the textual units.
- Observe their values on the different factorial axes.
- Observe similarities (scalar product) between relationships and words (or group of words).

Characters/relationships vs axes

Sometimes, factorial axes can be interpreted with coordinates of the words. Positions of characters/relationships on this axis reflect polarities on this scale:

1st axis, top 5 positive words	1st axis, top 5 positive relationships
poupée	Cosette – Simplice
religieuse	Grantaire – Simplice
maire	Fantine – Simplice
sœur	Simplice – Valjean
bougie	Magloire – Valjean
1st axis, top 5 negative words	**1st axis, top 5 negative relationships**
infanterie	Bahorel – Javert
cuirassier	Enjolras – Fauchelevent
brigade	Combeferre – Faucelevent
batterie	Feuilly – Javert
division	Feuilly – Valjean

6th axis, top 5 positive words	6th axis, top 5 positive relationships
accusé	Cochepaille – Javert
président	Chenildieu – Javert
avocat	Chenildieu – Cochepaille
huissier	Brevet – Cochepaille
juge	Chenildieu – Valjean
6th axis, top 5 negative words	**6th axis, top 5 negative relationships**
infini	Fauchelevent – Gillenormand
parfum	Dahlia – Fameuil
astre	Fameuil – Zéphine
luxembourg	Listolier – Zéphine
amour	Dahlia – Listolier

Characters/relationships vs words

We can also get the similarities between characters/relationships vs words with the scalar product:

Cosette	Cosette-Marius	Cosette-Valjean	Marius	Valjean
poupée (0.74)	noce (1.96)	noce (1.08)	théodule (0.66)	mestienne (0.57)
noce (0.7)	marié (1.4)	mestienne (1.05)	vernon (0.57)	fossoyeur (0.52)
mestienne (0.62)	mariage (1.39)	marié (0.75)	ursule (0.57)	accusé (0.51)
marié (0.5)	baron (1.11)	corbillard (0.71)	tante (0.55)	maire (0.41)
seau (0.49)	marier (1.03)	mariage (0.71)	noce (0.54)	gervai (0.41)
infanterie (-0.58)	brigade (-0.55)	infanterie (-0.59)	wellington (-0.39)	infanterie (-0.53)
cuirassier (-0.56)	hougomont (-0.54)	cuirassier (-0.57)	plateau (-0.39)	wellington (-0.53)
wellington (-0.55)	cuirassier (-0.53)	wellington (-0.56)	blücher (-0.38)	cuirassier (-0.52)
blücher (-0.52)	escadron (-0.53)	blücher (-0.53)	sacrement (-0.38)	blücher (-0.5)
division (-0.5)	division (-0.53)	brigade (-0.51)	guide (-0.37)	brigade (-0.48)
Marius-Valjean	**Javert**	**Javert-Valjean**	**Myriel**	**Myriel-Valjean**
noce (1.33)	accusé (1.72)	accusé (2.12)	conventionnel (7.27)	chandelier (6.28)
marié (0.91)	arras (1.22)	avocat (1.29)	évêque (3.98)	gendarme (5.06)
mariage (0.91)	avocat (1.13)	preuve (1.25)	hôpital (2.57)	panier (4.72)
tableau (0.78)	mouchard (1.1)	président (1.23)	cathédrale (2.57)	couvert (4.64)
baron (0.77)	preuve (1.08)	forçat (1.12)	curé (2.47)	deuil (4.52)
wellington (-0.49)	infanterie (-0.49)	infanterie (-0.51)	cuirassier (-0.64)	blücher (-0.85)
hougomont (-0.48)	wellington (-0.47)	cuirassier (-0.5)	infanterie (-0.59)	infanterie (-0.78)
blücher (-0.47)	cuirassier (-0.47)	brigade (-0.5)	bayonnette (-0.55)	charte (-0.77)
brigade (-0.47)	brigade (-0.47)	wellington (-0.49)	assaillant (-0.55)	prussien (-0.76)
cuirassier (-0.47)	sacrement (-0.46)	hougomont (-0.47)	batterie (-0.54)	berge (-0.74)

Words vs characters/relationships

By transposing the previous table, particular words (or group of words, i.e. a query) can give a ranking of characters/relationships:

aimer	rue	justice	guerre
Gillenormand-Mabeuf (1.15)	Cosette-Gavroche (0.79)	Babet-Javert (1.09)	Combeferre-Fauchelevent (1.35)
Dahlia-Fameuil (1.12)	Courfeyrac-Fauchelevent (0.79)	Babet-Magnon (1.09)	Enjolras-Fauchelevent (1.35)
Dahlia-Listolier (1.12)	Eponine-Fauchelevent (0.79)	Brujon-Claquesous (1.09)	Feuilly-Javert (1.33)
Fameuil-Zéphine (1.12)	Eponine-Gavroche (0.79)	Brujon-Javert (1.09)	Feuilly-Marius (1.33)
Listolier-Zéphine (1.12)	Gavroche-Valjean (0.73)	Brujon-Magnon (1.09)	Feuilly-Valjean (1.33)
Bahorel-Javert (-0.54)	Brevet-Chenildieu (-0.38)	Dahlia-Fameuil (-0.46)	Javert-Simplice (-0.6)
Babet-Grantaire (-0.45)	Brevet-Cochepaille (-0.38)	Dahlia-Listolier (-0.46)	Myriel-Valjean (-0.56)
Brujon-Gavroche (-0.45)	Champmathieu-Chenildieu (-0.38)	Fameuil-Zéphine (-0.46)	Magloire-Myriel (-0.53)
Brujon-Grantaire (-0.45)	Champmathieu-Cochepaille (-0.38)	Listolier-Zéphine (-0.46)	Magloire-Valjean (-0.51)
Gavroche-Gueulemer (-0.45)	Chenildieu (-0.38)	Azelma-Eponine (-0.4)	Baptistine-Magloire (-0.51)

In this case, the centroid method seems to show its limit.

Correspondence Analysis - Regressions

Relationship embeddings - 1st idea problems

In fact, building these character/relationship vectors as centroids is like considering them as supplementary variables in the CA. It leads to additive relationships, i.e., for a character c

$$v_c = \sum_{d \in \text{characters}} v_{cd}$$

where v_{cd} is the vector of relationship between c and d, and v_{cc} is defined as the centroid of units where c is alone. It means that:

- If a character have contrasted relationships, its vector might represent it poorly.
- If two characters are often together, their respective specificities might be hidden.
- If two relationships are often together, their respective specificities might be hidden.

Are we the sum of our relationships (+ ourself alone)?

Relationship embeddings - 2nd idea

A way to avoid this problem, is to consider that

- The appearance of character c **alone** gives a particular profile to units.
- The appearance of character d **alone** gives another profile to units.
- The appearance of character c **and** d might give a totally **different profile** to units.

We can use a **regression model**.

Relationship embeddings - 2nd idea

Let $(y_1, \ldots, y_n)$ be the coordinates of the n units on the **first factorial axis**, $\delta(c)$ the indicator variable of character c presence, and $\delta(c, d)$ the indicator variable of relationship c, d presence. We can fit the model:

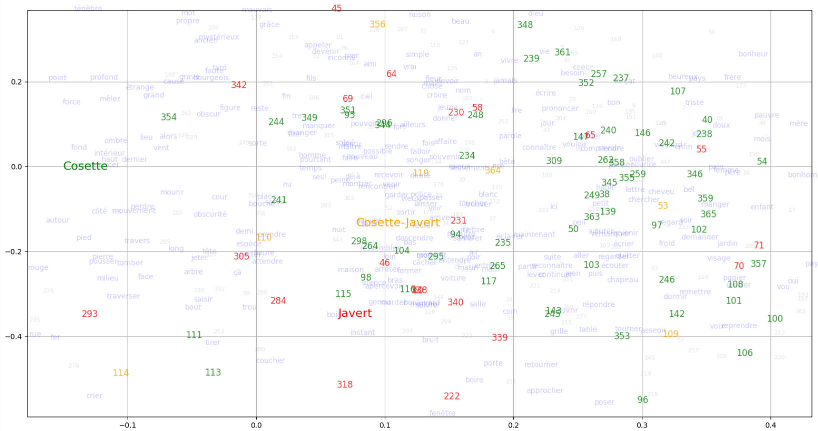
$$\hat{y} = \beta_0 + \sum_{c} \beta_c \delta(c) + \sum_{c,d} \beta_{cd} \delta(c, d)$$

with a **Ridge (L2) regularization term**, parameterized by λ, to avoid overfitting.

- The first coordinate of a **character-vector c is given by β_c**.
- The first coordinate of a **relationship-vector (c, d) is given by β_{cd}**.

We do a **similar regression on all axis to get vectors**.

Resulting coordinates point at different directions:



Relationship embeddings - 2nd idea

The regularizing parameter λ has an interesting effect on resulting vectors:

- When λ is high, the vectors are similar to centroids (with a different scaling).
- When λ is low, the solution focuses on very specific, small parts of the text to define characters and relationships.
- An average λ (but which one?) is able to highlight character/relationship specificities while using sufficient information.

Characters/relationships vs words - comparisons

With regressions, there is more variety in words defining characters/relationships:

Centroids

Cosette	Cosette-Marius	Cosette-Valjean	Marius	Valjean
poupée (0.74)	noce (0.7)	noce (0.7)	théodule (0.66)	mestienne (0.57)
noce (0.7)	marié (1.4)	mestienne (1.05)	vernon (0.57)	fossoyeur (0.52)
mestienne (0.62)	mariage (1.39)	marié (0.75)	ursule (0.57)	accusé (0.51)
marié (0.5)	baron (1.11)	corbillard (0.71)	tante (0.55)	maire (0.41)
seau (0.49)	marier (1.03)	mariage (0.71)	noce (0.7)	gervai (0.41)
Marius-Valjean	**Javert**	**Javert-Valjean**	**Myriel**	**Myriel-Valjean**
noce (1.33)	accusé (1.72)	accusé (2.12)	conventionnel (7.27)	chandelier (6.28)
marié (0.91)	arras (1.22)	avocat (1.29)	évêque (3.98)	gendarme (5.06)
mariage (0.91)	avocat (1.13)	preuve (1.25)	hôpital (2.57)	panier (4.72)
tableau (0.78)	mouchard (1.1)	président (1.23)	cathédrale (2.57)	couvert (4.64)
baron (0.77)	preuve (1.08)	forçat (1.12)	curé (2.47)	deuil (4.52)

Regressions

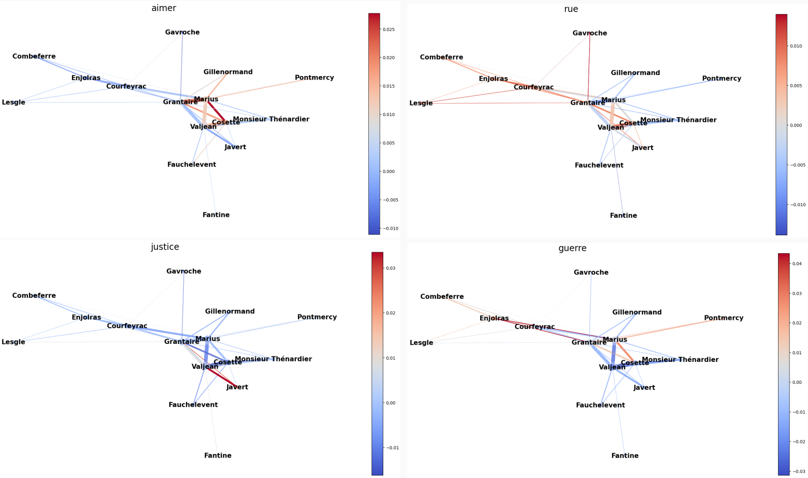
Cosette	Cosette-Marius	Cosette-Valjean	Marius	Valjean
poupée (0.52)	noce (0.49)	mestienne (0.35)	jondrette (0.61)	fossoyeur (0.51)
seau (0.5)	mariage (0.38)	noce (0.35)	réchaud (0.53)	mestienne (0.46)
gargote (0.3)	marié (0.36)	corbillard (0.29)	ursule (0.5)	gervai (0.43)
ravissant (0.29)	amant (0.33)	marié (0.26)	luxembourg (0.46)	chandelier (0.38)
auprès (0.27)	mardi (0.29)	babylone (0.24)	bouge (0.41)	matelas (0.34)
Marius-Valjean	**Javert**	**Javert-Valjean**	**Myriel**	**Myriel-Valjean**
égout (0.41)	arras (0.74)	accusé (0.49)	conventionnel (1.49)	chandelier (0.19)
noce (0.4)	roue (0.51)	nier (0.29)	évêque (0.73)	deuil (0.15)
issue (0.36)	malle (0.46)	avocat (0.28)	cathédrale (0.49)	gendarme (0.15)
galerie (0.35)	cabriolet (0.44)	forçat (0.26)	curé (0.44)	panier (0.15)
couloir (0.34)	accusé (0.44)	preuve (0.26)	hôpital (0.43)	couvert (0.13)

Words vs characters/relationships - regression

And characters/relationships according to words seems more adjusted:

aimer	rue	justice	guerre
Cosette-Marius (0.16)	Courfeyrac (0.11)	Javert-Valjean (0.17)	Enjolras (0.15)
Cosette (0.12)	Enjolras (0.1)	Javert (0.15)	*intercept* (0.15)
Marius (0.1)	Grantaire (0.1)	Grantaire (0.1)	Grantaire (0.14)
Myriel (0.07)	Gavroche (0.08)	Champmathieu-Valjean (0.08)	Enjolras-Marius (0.09)
Gillenormand (0.07)	Cosette-Javert (0.07)	Champmathieu (0.08)	Cosette-Javert (0.05)
Enjolras (-0.08)	Fantine (-0.06)	Cosette (-0.11)	Valjean (-0.23)
Javert-Valjean (-0.06)	Myriel (-0.06)	Gavroche (-0.07)	Cosette (-0.14)
Grantaire (-0.06)	Grantaire-Valjean (-0.06)	Marius (-0.07)	Monsieur Thénardier (-0.12)
Javert (-0.06)	Fantine-Valjean (-0.06)	Gervais-Grantaire (-0.06)	Grantaire-Marius (-0.12)
Monsieur Thénardier-Valjean (-0.05)	Cosette-Marius (-0.04)	Fantine-Gervais (-0.06)	Magloire (-0.09)

Words vs characters/relationships - regression



Words vs characters/relationships - regression

This method give also good results if regressors are constructed according to a narrative time division (here, *tomes*):

T1	T2	T3	T4	T5
arras (0.16)	cuirassier (0.26)	jondrette (0.16)	argot (0.14)	égout (0.18)
évêque (0.15)	wellington (0.25)	réchaud (0.13)	hucheloup (0.12)	cloaque (0.15)
conventionnel (0.15)	infanterie (0.25)	vernon (0.12)	émeute (0.12)	sable (0.15)
oratoire (0.14)	brigade (0.24)	théodule (0.12)	lafayette (0.11)	berge (0.14)
maire (0.14)	hougomont (0.23)	tableau (0.11)	philippe (0.11)	galerie (0.12)
Cosette-Valjean T1	**Cosette-Valjean T2**	**Cosette-Valjean T3**	**Cosette-Valjean T4**	**Cosette-Valjean T5**
religieuse (0.05)	mestienne (0.18)		babylone (0.07)	noce (0.13)
médecin (0.04)	corbillard (0.13)		plumet (0.05)	marié (0.1)
maire (0.04)	fossoyeur (0.12)		luxembourg (0.05)	mariage (0.09)
pardon (0.03)	cimetière (0.11)		miroir (0.04)	mardi (0.07)
soeur (0.03)	bière (0.09)		promenade (0.04)	baron (0.06)

Quick summary

To recap from here:

- Words and units vectors are obtained from the unit-term matrix.
- Characters/Relationships vectors are obtained with 2 different methods:
    - Centroids
    - Regressions
- These character/relationship vectors can be explored regarding:
    - Axes
    - Words (or group of words)
- Moreover, character/relationship vectors can be constructed according to a time division.

Other types of Embeddings

Pre-trained Word Embeddings - justifications

CA is a constrastive analysis: the units, words, and characters/relationships are constructed relatively to the author style and subject.

It can be interesting to get insights on how characters/relationships are perceived in an absolute referential.

To perform this idea, units/characters/relationships are embedded in a pre-trained word embedding space.

Pre-trained Word Embeddings

Type-based embeddings (no transformers) must be used, because we would like to have reference points, such as the word vectors, to explore results.

Some examples of type-based embedding methods:

- Word2Vec [Mikolov et al., 2013]
- GloVe [Pennington et al., 2014]
- FastText [Bojanowski et al., 2017]

Here, we will use pre-trained word vectors constructed with FastText `https://fasttext.cc/docs/en/crawl-vectors.html`.

Pre-trained Word Embeddings

There also exists various ways to construct **sentences, paragraphs, or documents embeddings** (in our case units) into the **same space as words**.

The method proposed by [Arora et al., 2017] seems to perform very well in various tasks. Quickly explained:

- Units are embedded by making the average of their words, **weighted by $\frac{\theta}{\theta+f_w}$**, where f_w is the word frequency and θ a "smoothing parameter".
- We **substract** from all vectors, contained in the columns of $\mathbf{X}$, their projection alongside the first (left) singular vector of $\mathbf{X}$.

The first operation gives more importance to **rare words**, the second helps to remove **syntactic information**.

Embedding of characters/relationships is obtained again with centroids and regressions. The cosine similarity is used to measure characters/relationships affinities with words:

Cosette	Cosette-Marius	Cosette-Valjean	Marius	Valjean
blottir (0.37)	sincère (0.38)	rue (0.46)	regarder (0.38)	jean (0.6)
tourbillonner (0.37)	honnêteté (0.36)	faubourg (0.42)	entrouvrir (0.36)	pantalon (0.33)
bercer (0.34)	amour (0.35)	boulevard (0.41)	étreindre (0.34)	boutonner (0.3)
étreindre (0.34)	éternel (0.34)	jean (0.39)	voir (0.34)	jacques (0.27)
caresser (0.33)	désir (0.33)	avenue (0.38)	refermer (0.33)	claude (0.26)
fonctionnaire (-0.39)	rebord (-0.41)	aspirer (-0.33)	roi (-0.39)	empereur (-0.29)
militaire (-0.39)	ruelle (-0.41)	absorber (-0.32)	évêque (-0.37)	rossignol (-0.28)
ecclésiastique (-0.39)	mur (-0.4)	effleurer (-0.31)	seigneur (-0.37)	souverain (-0.28)
magistrat (-0.38)	rue (-0.4)	gonfler (-0.3)	république (-0.37)	noble (-0.27)
sénateur (-0.38)	couloir (-0.38)	étouffer (-0.3)	empereur (-0.36)	lettré (-0.27)
Marius-Valjean	**Javert**	**Javert-Valjean**	**Myriel**	**Myriel-Valjean**
égout (0.4)	aller (0.39)	mépris (0.35)	évêque (0.59)	étreindre (0.38)
berge (0.39)	déplacer (0.36)	doctrinaire (0.33)	archevêque (0.54)	âme (0.36)
souterraine (0.37)	galoper (0.35)	autorité (0.3)	ecclésiastique (0.46)	étinceler (0.35)
souterrain (0.35)	rouler (0.33)	criminel (0.29)	prêtre (0.45)	amour (0.33)
pont (0.35)	parcourir (0.32)	oppression (0.29)	vicaire (0.43)	caresse (0.32)
gentil (-0.29)	bienheureux (-0.3)	aller (-0.36)	jambe (-0.31)	système (-0.32)
consoler (-0.28)	père (-0.28)	repartir (-0.34)	fenêtre (-0.3)	plan (-0.3)
parent (-0.26)	poison (-0.28)	galoper (-0.31)	ruelle (-0.3)	cours (-0.29)
père (-0.26)	éclatant (-0.28)	dormir (-0.31)	rue (-0.29)	début (-0.28)
demander (-0.26)	éclat (-0.28)	emmener (-0.29)	tôle (-0.29)	retard (-0.27)

Pre-trained Word Embeddings

Still a work in progress. However, we can see that:

- The found words are less specific to the text (easier to make a general interpretation).
- Some characters/relationships are mainly defined by verbs, others by nouns, and others by adjectives.
- The negative words actually give information.

More importantly, the characters/relationships are in an absolute space, comparison between works should be made.

Non-negative matrix factorization

The last idea is Non-negative Matrix Factorization, which is a Topic Modeling method.

Its usage permits to get associations between characters/relationships and automatically found topics (not only words).

As the method gives probabilities of using each topic, for all units, character/relationship embeddings have to be adapted:

- Centroid $\rightarrow$ Probability Chain Rule.
- Regression $\rightarrow$ Multinomial Logistic Regression.

Non-negative matrix factorization

This method seems promising, but, for the moment, not as accurate as the other two:

						Cosette	Cosette-Marius	Cosette-Valjean	Marius	Valjean
T1	monsieur	enfant	aller	père	homme	5.74%	0.48%	0.76%	12.78%	15.91%
T2	barricade	rue	fusil	pavé	insurgé	8.32%	0.07%	0.87%	4.05%	3.23%
T3	peuple	révolution	droit	homme	france	0.53%	59.36%	8.07%	6.22%	12.67%
T4	égout	paris	rue	ville	cloaque	1.13%	0.00%	6.37%	0.97%	5.46%
T5	jean	homme	pouvoir	rue	venir	11.95%	0.11%	0.12%	1.31%	35.05%
T6	anglais	bataille	wellington	napoléon	waterloo	1.73%	1.55%	9.00%	1.25%	1.86%
T7	évèque	monsieur	curé	dieu	digne	8.34%	3.66%	0.05%	0.17%	10.06%
T8	couvent	mère	religieux	prieur	saint	0.80%	34.31%	73.24%	1.41%	3.25%
T9	jondrette	porte	fille	neige	aller	5.40%	0.00%	0.10%	34.98%	3.73%
T10	amour	fille	jeune	banc	âme	56.06%	0.46%	1.42%	36.87%	8.78%
						Marius-Valjean	**Javert**	**Javert-Valjean**	**Myriel**	**Myriel-Valjean**
T1	monsieur	enfant	aller	père	homme	0.23%	62.35%	0.01%	2.14%	0.13%
T2	barricade	rue	fusil	pavé	insurgé	3.91%	2.55%	1.30%	0.33%	0.56%
T3	peuple	révolution	droit	homme	france	1.31%	0.47%	66.28%	20.62%	1.71%
T4	égout	paris	rue	ville	cloaque	77.54%	3.57%	0.31%	0.60%	0.49%
T5	jean	homme	pouvoir	rue	venir	1.06%	5.33%	0.08%	0.02%	2.48%
T6	anglais	bataille	wellington	napoléon	waterloo	12.57%	22.21%	0.14%	3.44%	0.93%
T7	évèque	monsieur	curé	dieu	digne	1.66%	1.33%	0.85%	64.90%	0.64%
T8	couvent	mère	religieux	prieur	saint	0.08%	0.10%	3.88%	1.34%	41.41%
T9	jondrette	porte	fille	neige	aller	0.13%	1.61%	0.01%	0.03%	0.26%
T10	amour	fille	jeune	banc	âme	1.52%	0.49%	27.14%	6.58%	51.40%

Conclusion

Conclusion

The proposed framework to analyse characters and relationships seems promising:

- Works on various corpus size.
- Works with various type of textual units (e.g., lines in plays).
- Works with oriented relationships.
- Two types of character/relationship construction.
- Multiple ways to explore the results.

However, some remarks:

- Choices in pre-processing (stop words, lemmatization, thresholds on word frequencies, thresholds on character occurrences) can strongly affect results.
- Hyperparameters can be hard to tune.
- Results can be hard to interpret.
- How can we know for sure that results are accurate?

Thank you for your attention !

Questions ?

References

Arora, S., Liang, Y., and Ma, T. (2017).
A simple but tough-to-beat baseline for sentence embeddings.
In *International conference on learning representations*.

Bojanowski, P., Grave, E., Joulin, A., and Mikolov, T. (2017).
Enriching Word Vectors with Subword Information.
Transactions of the Association for Computational Linguistics, 5:135–146.

Elsner, M. (2012).
Character-based kernels for novelistic plot structure.
In *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*, pages 634–644, Avignon, France. Association for Computational Linguistics.

Labatut, V. and Bost, X. (2019).
Extraction and Analysis of Fictional Character Networks: A Survey.
ACM Computing Surveys, 52(5):89:1–89:40.

Lebart, L., Pincemin, B., and Poudat, C. (2019).
Analyse des données textuelles.
Number 11 in Mesure et évaluation. Presses de l'Université du Québec, Québec.

Mikolov, T., Chen, K., Corrado, G., and Dean, J. (2013).
Efficient Estimation of Word Representations in Vector Space.
arXiv:1301.3781 [cs].
arXiv: 1301.3781.

Min, S. and Park, J. (2019).
Modeling narrative structure and dynamics with networks, sentiment analysis, and topic modeling.
PLOS ONE, 14(12):e0226025.

Nalisnick, E. T. and Baird, H. S. (2013).
Character-to-Character Sentiment Analysis in Shakespeare's Plays.
In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 479–483, Sofia, Bulgaria. Association for Computational Linguistics.

Pennington, J., Socher, R., and Manning, C. (2014).
Glove: Global Vectors for Word Representation.
In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1532–1543, Doha, Qatar. Association for Computational Linguistics.

Rochat, Y. and Kaplan, F. (2014).
Analyse des réseaux de personnages dans Les Confessions de Jean-Jacques Rousseau.
Les Cahiers du numérique, 10(3):109–133.
Place: Cachan Publisher: Lavoisier.

Trovati, M. and Brady, J. (2014).
Towards an Automated Approach to Extract and Compare Fictional Networks: An Initial Evaluation.
In *2014 25th International Workshop on Database and Expert Systems Applications*, pages 246–250, Munich, Germany. IEEE.