Refining Character Relationships in a Textual Narrative using Embeddings of Interactions

With case studies on *Les Misérables*

Guillaume Guex

University of Lausanne

Table of contents

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 **textual narratives**, 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

⋮

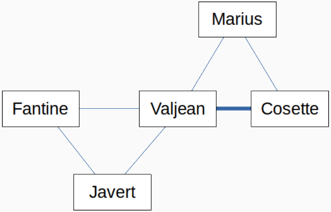
Lorsque Jean Valjean, dans la nuit même du jour où Javert l'arrêta près du lit de mort de Fantine, s'échappa de la prison municipale de Montreuil-sur-Mer,...

⋮

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 the embedding of textual units.

Approaches

More specifically, two types "embeddings" are studied:

- **Correspondence Analysis (CA)**.
- **"Topic Modeling vectors"** build from **Non-negative Matrix Factorization (NMF)**.

With two methods for constructing character/relationship vectors:

- **Centroids**.
- **Regression coefficients**.

Correspondence Analysis (CA) - centroids

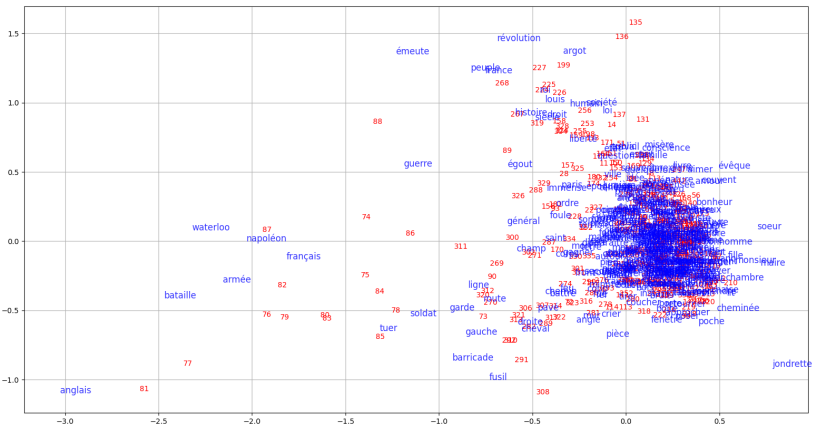
Principles

Correspondence Analysis is the natural tool for analyzing textual resources if data are 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 similar profile in term of words.
- **Coordinates of each word** along the same factors, where proximity can be interpreted as similar profile in term of documents.
- **Affinities between a document and a term**, which is computed by the **scalar product** between their vectors.

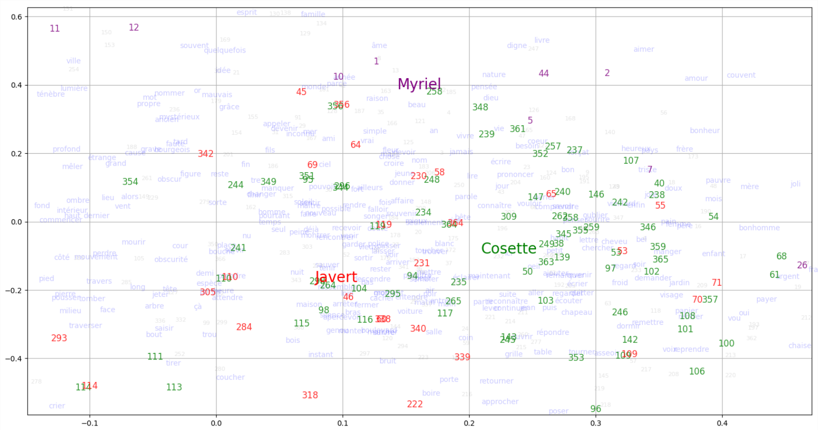
Principles

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



Characters embeddings - centroids

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.



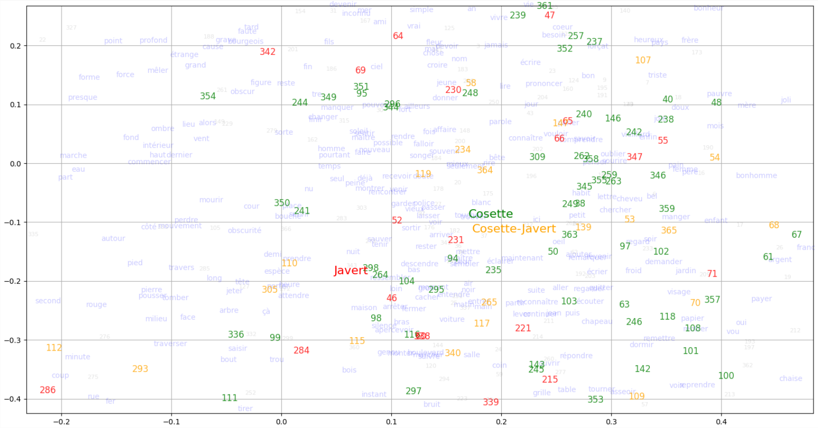
Relationship embeddings - centroids

The same idea can be applied to **relationships**, In fact, in our data table, we can extend our table to include **interactions**.

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

Relationship embeddings - centroids

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 their affinity with this particular scale:

1st axis, top 5 positive words	1st axis, top 5 positive relationships	6th axis, top 5 positive words	6th axis, top 5 positive relationships
poupée (doll)	Cosette – Simplice	accusé (accused)	Cochepaille – Javert
religieuse (religious)	Grantaire – Simplice	président (president)	Chenildieu – Javert
maire (mayor)	Fantine – Simplice	avocat (lawyer)	Chenildieu – Cochepaille
sœur (sister)	Simplice – Valjean	huissier (bailiff)	Brevet – Cochepaille
bougie (candle)	Magloire – Valjean	juge (judge)	Chenildieu – Valjean
1st axis, top 5 negative words	**1st axis, top 5 negative relationships**	**6th axis, top 5 negative words**	**6th axis, top 5 negative relationships**
infanterie (infantry)	Bahorel – Javert	infini (infinity)	Fauchelevent – Gillenormand
cuirassier (cuirassier)	Enjolras – Fauchelevent	parfum (scent)	Dahlia – Fameuil
brigade (brigade)	Combeferre – Faucelevent	astre (heavenly body)	Fameuil – Zéphine
batterie (battery)	Feuilly – Javert	luxembourg	Listolier – Zéphine
division (division)	Feuilly – Valjean	amour (love)	Dahlia – Listolier

Characters/relationships vs words

We can also get the **similarities between characters/relationships vs words** with the help of 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 (CA) - regressions

Relationship embeddings - 1st idea problems

In fact, building these character/relationship vectors as **centroids** is like considering them as **additional 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. This means

- 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 with interaction**.

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:

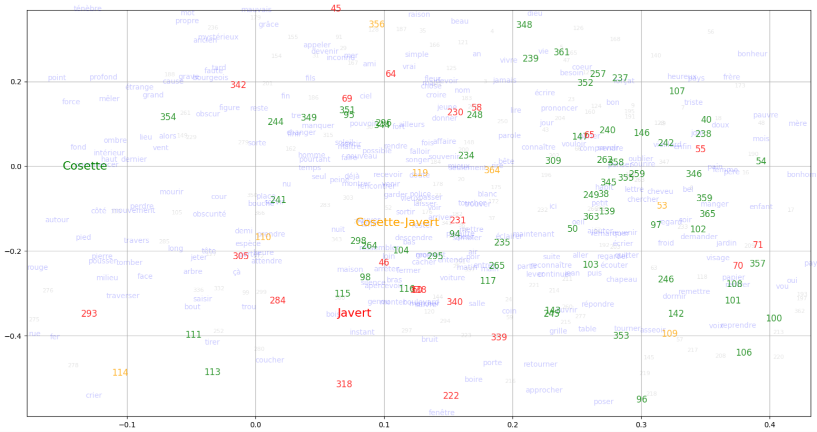
$$\hat{y} = \beta_0 + \sum_{c} \beta_c \delta(c) + \sum_{c,d} \beta_{cd} \delta(c, d)$$

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 of opposite characters 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 relatively to corpus size.**

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 relationships according to words are more coherent:

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

This method give also good results if regressors are constructed according to a **narrative timeline** (here, the *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)

CA quick summary

To recap the CA method:

- **Words and units vectors** are obtained from the **unit-term matrix**.
- **Characters/Relationships vectors** are obtained with 2 different methods:
    - **Centroids**
    - **Regressions**
- These characters/relationships vectors can be **explored** regarding:
    - **Axes**
    - **Words** (or group of words)
    - **According to timeline**

Pre-trained Word 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**.

An idea to overcome this problem is to embed units/characters/relationships in a **absolute referential** such as a **pre-trained word embedding space**.

References

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.

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.

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.