Factors of Literary History: The Case of German-language Poetry (1850–1920)

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Introduction

Many researchers emphasize that in order to adequately understand literature and literary change, it is crucial to consider the numerous relations that exist between (aspects of) literary texts and between literary texts and extra-literary factors (e.g. Ort 1991, Titzmann 1991). Yet which specific relations are relevant is a matter of differing theories (cf. Engel 2018, Kalliney 2019). The question is how to find out, in a methodologically controlled way, for a given literary phenomenon, which factors are related to and influence the phenomenon in the first place, how to weigh the factors, and how to take into account that the factors may influence each other. The aim of this paper is to contribute to this fundamental question from the perspective of Computational Literary Studies by discussing two consecutive approaches and applying them to an example from literary history. Our use case is the representation of emotions in German-language poetry from about 1850 to 1920. We seek to investigate to what extent different factors, especially the literary period, influenced what kinds of emotion were represented.

Resources

Our corpus consists of 6619 poems from 22 anthologies, published between 1859 and 1919. 8 anthologies represent the poetry of realism, 12 anthologies the poetry of early modernism and 2 anthologies the period of expressionism.

We annotated 1352 poems[1]from our corpus for emotion and genre. The annotators used a list of 6 discrete emotions (agitation, anger, fear, love, joy, sadness), inspired by the emotion hierarchy in (Shaver et al. 1987). The inter-annotator agreement, measured with γ (Mahet et al. 2015), was 0.7491. We also annotated what kind of entity experienced the emotion: the speaker, another character, or an object. For genre annotation, we distinguished 8 thematic genres (love poetry, nature poetry, etc.) and 4 non-thematic genres (ballad, elegy, song, sonnet). The agreement was 0.69 (Krippendorff's alpha). More detailed information on annotation can be found in previous papers from our working group (Konle et al. 2022; annotation guidelines: Kröncke et al. 2022a, Kröncke et al. 2022b). For all experiments only the annotated texts are used.

Formal Modeling of the Factors

A formal modeling of factors which influence literary history has only started recently to our knowledge. Underwood et al. 2022 analyze rd. 10.000 volumes, published between 1880 and 1999 using a three-factor model of change: author age, generational cohort and historical period, and conclude that "differences between cohorts explain slightly more than half of literary change" (Underwood 196). A formal modeling of cultural evolution is far more common (e.g. Hyafil and Baumard 2022).

Our approach is heavily indebted to the Bayesian analysis as outlined in McElreath 2020. It allows us to see the factors in the logistic regression model as following distributions instead of just single values. Even more important for us are the proposed approaches on how to handle assumptions about causal relations between the factors in the analysis.

Approach I

It is necessary to determine and justify which factors for the literary phenomenon should be analyzed. We have chosen period, author gender (female=1, male=0), thematic genre (TG), non-thematic genre (NTG), and experiencing entity as potential factors influencing which emotions are represented in a poem. This choice is based partly on previous research that has suggested such relationships (Konle et al. 2022), partly on theoretical considerations, and partly on data availability.

Our first approach uses a logistic regression model denoted by the formula below:

$a_{[e]} \sim \mathrm{Normal}(0,1)$

$b_{[e,f]} \sim \mathrm{Normal}(0,1)$

$u_{[e]} \sim a_{[e]} + \mathrm{dot}(b_{[e,f]}, x_{[e,f]})$

$\theta_{[e]} \sim \mathrm{softmax}(u_{[e]})$

$y \sim \mathrm{cat}(\theta_{[e]})$

The model contains an intercept a for each emotion [e] and slopes b for each factor [f] and emotion. # is the probability distribution over all emotions.

After fitting the model to our dataset we want to measure the influence of each factor. Therefore we sample from posterior (fitted) values of b and calculate the mean of their modulo (see Table 1).

Tab. 1: Direct impact and standard deviation of feature groups on emotion distribution.

Feature	Period	Gender	TG	NTG	Entity
Influence	.22 (.16)	.15 (.08)	.27 (.15)	.26 (.16)	.33 (.22)

Approach II

The logistic regression model described above treats all features equally. This behavior can lead to erroneous conclusions, since there are likely interactions between factors. Before these problems can be addressed, we need to be clear on a purely conceptual level about the relationship in the data of our model. We denote those relationships as a Causal DAG[2] (Fig. 1). It reads as follows: The feature node gender is influenced by period via the edge p2 and influences, among others, emotion via g1.

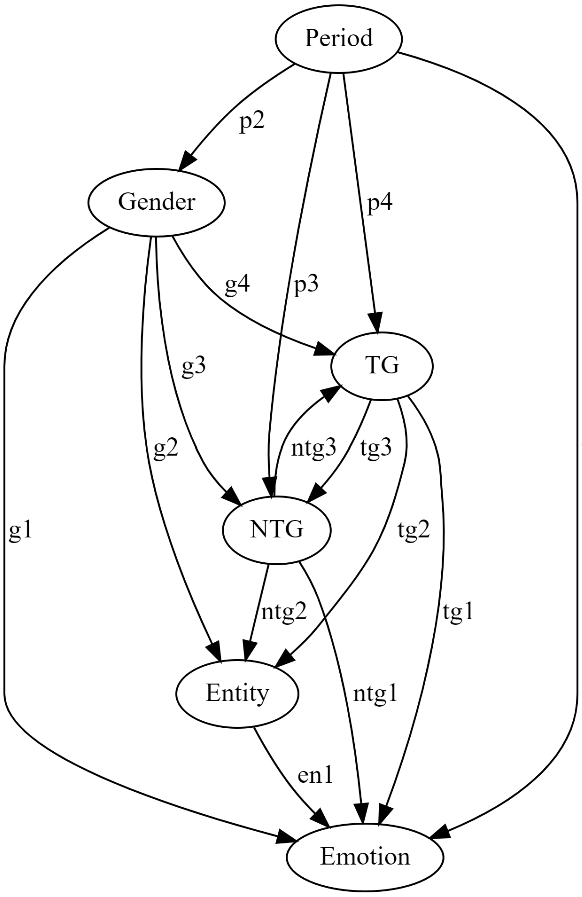

Figure 1. Causal Dag

If we are interested in the influence of entities on emotions (edge en1), we need to check which features influence (confound) entities, because these features could pass their influence unseen through the entity feature (mediator) and corrupt our findings. This is true for gender, TG and NTG. We need to address this hidden influence by conditioning on these confounders. Conditioning in the context of regressions simply means adding to the model. Since gender, TG and NTG are already in our model, we can trust the estimated influence of entities from Tab. 1.

Unfortunately, this is not the case for the other features. Conditioning on gender does allow us to measure the influence of its mediator entity, but conditioning on a mediator does not allow us to measure the influence of its confounder. The influence of gender from Tab. 1 just resamples its direct influence[3] (g1), but its total influence is the sum of g1-4. To measure total influence we need to “block” the indirect information flow of g2-4 and condition on the confounder epoch. This may seem reductive, but is necessary, since total influence can be entirely different to direct influence[4].

Excluding mediators and conditioning confounders for each feature leads to the total influence values in Table 2.

Tab. 2: Total impact and standard deviation of feature groups on emotion distribution.

Feature	Period	Gender	TG [5]	NTG	Entity
Influence	.23 (.11)	.21 (.13)	.28 (.19)	.27 (.22)	.33 (.22)

The results suggest that factors ‘close to the text’ (genre, entity) have a somewhat greater impact on emotion than factors more ‘distant from the text‘ (period, gender).

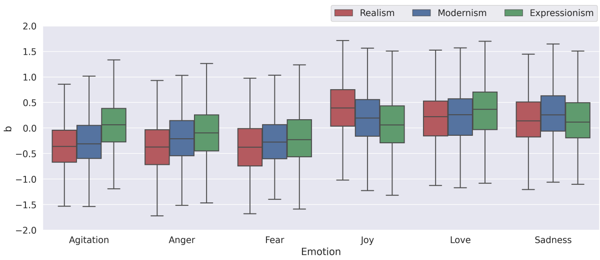

Figure 2: Posterior b values for period factors and emotions.

Focusing on period as a factor, we see that negative emotions (anger, fear) increase and joy decreases. For these emotions, the development is roughly linear, but there are exceptions: sadness, for example, increases from realism to modernism, but decreases again toward expressionism.

Discussion

The proposed model is by no means complete and therefore likely erroneous due to untracked factors and confounders (eg. general language change, register, more author based factors such as generational cohort, and more types of genres).

Notes

1. Code and Data: https://github.com/LeKonArD/Factors-of-Literary-History-The-Case-of-German-language-Poetry
2. Directed Acyclic Graph
3. Direct influence can be seen as influence if everything else is held constant.
4. Simpson's Paradox
5. Since TG and NTG are both confounder and mediator for each other, we can not distinguish their influence

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