Telling Stories of Transitions: A Demonstration of Nonlinear Epistemic Network Analysis

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Abstract. I demonstrate nonlinear modeling and clustering in extension to existing Quantitative Ethnography methods as an approach to telling stories of transitions. The Epistemic Network Analysis (ENA) algorithm is a three step process: it represents qualitative data as a high dimensional space that models the connections between qualitative codes; it uses multidimensional scaling to reduce the dimensionality of that space while highlighting features of interest; and it projects a network representation onto that scaled space as a way to illustrate the dynamics of those features. Existing multidimensional scaling algorithms used by ENA have been linear, which have limitations in elucidating major life transitions as they are experienced: Such stories are nonlinear, with ebbs, flows, and structural breaks. Therefore, to capture such dynamics, I introduce Nonlinear ENA, which deviates from traditional ENA by using a nonlinear multidimensional scaling algorithm, and I demonstrate how one might tell a temporal story with Nonlinear ENA by telling the story of my first year on feminizing hormones.

Keywords: Epistemic Network Analysis · Nonlinear ENA · Analytic Autoethnography · Transitions · Transgender

1 Introduction

At the previous ICQE, I spoke with others who had interest in using Quantitative Ethnography (QE) to model stories that move over time. From my analytic autoethnographic work, I have such a story and a dataset, these pose interesting methodological concerns, and these have been central to my own coming to understand QE methodology.

In 2020, I began Hormone Replacement Therapy (HRT) [1]. I am transgender and a woman, and HRT was an important part of my gender and social transition. I kept extensive notes, which served three purposes. One, they allow changes to be seen that happen too gradually to notice otherwise. Two, they are a space for practicing and shaping conceptions of shifting identities. Three, they are analytic moments for developing theoretic sensitivity and perception of autoethnographic experiences under study [2].

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These notes have provided me an interesting dataset for examination during my journey with QE: This data is temporal, it has a simple structure otherwise, it has no *a priori* groups or clusters, and I am deeply and intrinsically motivated towards "getting the story right."

With this data, I asked: *How can QE be used to tell a temporal story?* One might ask a similar question of non-temporal data that still "moves" over a continuous variable [3]. Either way, such story-telling might have two subtasks: use QE to provide evidence of saturation, and use QE to tell a rich qualitative story whose turns are guided by quantitative features.

Initial analysis using QE's existing linear modeling methods demonstrated two obstacles for this second subtask. One, there are parts of the story that it misses. Two, the story that it does tell is uninsightful to the point of being misleading. Incorporating nonlinear modeling into my analytical process resolved those issues.

In this paper, I demonstrate that extending existing QE methodology with a nonlinear projection algorithm (in this case UMAP) and a clustering algorithm (in this case DBSCAN) provides several affordances when working with temporal data. First, it allowed me to make systematic decisions about how to relate units with similar units nearby in time when I had no *a priori* structure. Second, it identified which of many qualitatively meaningful moments actually incurred a structural break. Third, it neatly modeled nonlinear behavior, where early on in the year I repeatedly started and stopped HRT. Fourth, it visualized the effect of that structural break on that nonlinear behavior. Fifth, these results were reflectively surprising, which promoted clearer theoretical thinking. Finally, these results provided not only grounded and saturated *content*, but also grounded and saturated *structure* by which to organize my narrative. In this way, the nonlinear extension to existing QE methods allowed me to tell a richer, more informed story, without caricaturizing my transition experiences.

2 Relevant Theory

2.1 Analytic Autoethnography

Autoethnography allows examination of one's own experiences that would not otherwise be observable to other researchers [4, 5]. I am providing an account based on personal daily notes, which out of potential for embarrassment I would not be likely to share with another researcher, and I suspect there are other transwomen who feel the same given the current political climate in the United States around trans issues [6]. And in Analytic Autoethnography (AA), "authors seek to discover or better understand some aspect of their existence as communicable and applicable in abstracted form" [5], the purpose of which is to provide "structured analysis of one's own experiences with the intention of gaining broad social and cultural insights" [7]. Authors are free to choose a style of expression, such as evocative or analytical, as best suits their project needs. Given my aims of self-study and explicit analysis, AA is appropriate for this project.

To achieve self-study and explicit analysis, AA includes *inter alia* four tenets [8, 5]. One, the researcher must be a "complete member of the social world under study" [8]. I am a complete member researcher of the transwoman social world, and felicitously due to the COVID-19 pandemic, I have been able to connect remotely with other transwomen in ways I would not have been able to otherwise. Two, the researcher must be deeply aware of the reciprocal influence between themselves, the social world under study, and their analytical methods. I have been analytically reflexive as such, this project developing in tandem with my own learning of QE methods. Fleshing out the reciprocal influence between the two has been a powerful motivation this past year: I simultaneously sought deeper understanding into my own heavily politicized identity and to be able to back up that understanding with honest and flawless methods. Three, in AA works, the researcher must be a visible social actor, their own lived experiences incorporated into the story, and those experiences treated as data for analysis. I am the central social actor in the story told below, the only other actors relevant for this paper being occasional strangers and my doctor. Four, AA works must be committed to the agenda of "us[ing] empirical data to gain insight into some broader set of social phenomena" [8]. I am committed to the analytic agenda: "[O]urs is a collective and cumulative enterprise of knowledge" [5], so while I do not present this work as representative of all transwomen's experiences during their first years on HRT, nor do I present this work for the sake of theory-building about trans experiences, I do present it as a demonstration for how to work with temporal data in a way that does not caricaturize its participants, and I take seriously the task of "getting the story right" backed specifically by analytic methods.

2.2 Desire & Damage

In this work, I refuse to structure my story around gender dysphoria, trauma, or generally "damage." Research that starts from these positions is research that's "thinking of ourselves as broken" [9]. There is a long history of social-justice-oriented qualitative research that centers on "damage" done on the social worlds under study, underpinned by the theory of change that, by documenting loss, political gains can be obtained. However, this theory of change ignores the historical context and structural power struggles surrounding that ostensible damage: "After the research team leaves, after the town meeting, after the news cameras have gone away, all we are left with is the damage" [9].

I instead adopt a desire-based frame. Desire centers "complexity, contradiction, and the self-determination of lived lives," and it often flips scripts of blame and power [9]. This is not to say that desire-based frameworks are naively optimistic. They account for loss and despair just as well as they account for hope, vision, and communal wisdom. For example, my qualitative codes capture dysphoria and non-happiness just as well as longing, affirmation, coming out, and crying (these are happy tears), and in my analysis below, tensions between doubt and desire are front and center.

2.3 Transitions

Stories of transitions abound in healthcare and in life, such as becoming a parent, exiting sex work, and new jobs [10–12]. QE work has been done on transitions, but none whose models are grounded in a theory of transition as an *experience* [13, 14]. Transitions are marked by a number of essential properties, such as the following. First, subjects *engage* with transitions through information seeking, preparation, and so on; for example, my engagements included decisions about taking doses, reflections in daily notes, information seeking online and with my doctor, and this analytic autoethnographic project. Second, transitions result *from change* and result *in change*. Subjects may desire, confront, and have complex relationships with such changes. Third, transitions occur over *time spans*, and the bounds, stages, stability, continuity, ebb and flow, and linearity of a time span can be complex: "In evaluating transition experiences, it is important to consider the possibility of flux and variability over time" [10]; for example, the stages of my first year on HRT moved in jumps and spurts, some days dragging on, others flying by, and some caught in vicious cycles. Finally, transitions are pockmarked by *critical events* which can result in changes to stability, engagement, self-awareness, certainty, routines, and so on. Put another way, transitions contain "structural breaks," changes in qualitative central tendencies.

With these properties in mind, I will model time as a story composed of "types" of days, influenced in part by the march of time, and with no other *a priori* structure.

3 Methods

3.1 Context & Data Collection

On February 14th, 2020 I started feminizing hormone replacement therapy. This consisted of an initial consult with a doctor specializing in gender affirming care, daily doses of Spironolactone and Estradiol, occasional follow-ups with my doctor over Zoom, and occasional blood work to monitor my testosterone and estrogen levels. (As treatment plans are individualized, others' therapy may include other practices and/or medications [1].) In addition, over the year that followed, I kept notes in two forms, daily "checkboxes" of emerging themes and in-the-moment reflections in a notes app on my phone.

3.2 Qualitative Coding

On February 14th, 2021, a year after I started HRT, and in the days leading up to then, I re-read and inductively coded all daily notes using a grounded-theory inspired approach [15]. Some themes emerged in my notes during the year and were simplified to a checkbox. However, not all of these, in retrospect, were qualitatively insightful, and several were apparent only in the re-read. For example, an early code for "craving salt" provided no value, and I did not notice the salience of "spelling out recipes for makeup/etc." until the end. My goal during this inductive coding process was to model an honest and complete account of my experiences with HRT that first year. And as the sole coder, the logic is that I am providing a qualitative description that is *inherently perspectival*, not "objective," and so no inter-rater reliability checks were necessary [4, 16]. To limit implicit bias and expose inconsistencies during this coding process, data were triangulated with an assemblage of other media produced during and leading up to the year under study: text messages, selfies, old hand-written journals, browser histories, credit card transactions, and messages with my doctor [17, 4]. The resulting themes are defined in Table 1.

Table 1. Codebook

Label	N	Code	Example
`DoseTracking`	42	A journal entry tracking the exact time of an HRT does.	"7:35a e."
`Happy`	136	A checkbox marking days in which I felt happy.	18 Oct. 2020, when my partner and I were called "ladies" during a date downtown.
`NonHappy`	120	A checkbox marking days in which I felt a non-happy emotion, such as anxiety, depression, etc.	18 Oct. 2020, when my partner still called me "he" because I was not out to our friends yet.
`SkippedDose`	95	A checkbox marking days on which I skipped my HRT dose.	30 Jul.–16 Aug. 2020, when I had run low and would not be able to refill my prescriptions until the Fall semester.
`Sweets`	130	A checkbox marking days on which I craved sweets, such as chocolate or caffeinated drinks.	31 Aug. 2020, when I was too afraid to enter the make-up aisle at Target and bought and ate junk food instead.
`BODY`	153	A checkbox or journal entry tracking changes to my body, feelings, or behaviors.	A checkbox marking days on which my skin was oily, which estrogen has the effect of decreasing, or the entry, "Haven't felt [mental] fog in a while."
`LEARN`	56	A checkbox or journal entry tracking my efforts to self-teach about (trans)womanhood, such as through research or experimentation.	Citing hormone treatment guidelines from Boston University or the entry, "Tried something new with my makeup."
`REFLECT`	137	A checkbox or journal entry tracking my reflections with my identity as situated within or connected to various domains, such as family and religion.	"...looking at a photo of my grandma..." or "This is one of my favorite videos, [link], 'You have unconditional permission to be your ******* self'"
`PROGRESS`	88	A checkbox or journal entry tracking my progress towards my transition goals. (At my initial consult, I stated my goals as, "I value happiness, passing, and understanding," gesturing to suggest that understanding was the highest priority. After some experience, "passing" was redrawn as "safety.")	A checkbox marking days in which I passed in public, either by accident or on purpose, such as 18 Oct. 2020 when I passed downtown, or the entry, "Accepting myself as a woman makes sense."

3.3 Epistemic Network Analysis

Epistemic Network Analysis (ENA) was used to accumulate qualitative connections and construct an initial linear model of the year [18]. Units of analysis were defined as all events associated with a given day. The ENA algorithm typically uses a moving window to judge co-temporality when constructing a network model [19]. However, because each conversation in my data consists of a single line (the data associated with a given day), the size of the window used by the algorithm was moot.

In the initial linear model, the resulting networks were not aggregated, as the data lacked *a priori* groups. In the subsequent linear model informed by the clusters discussed below, the resulting networks were aggregated by cluster number.

The ENA model normalized the networks for all units before they were subjected to any dimension reductions. In the initial linear model, the reduction used singular value decomposition, which produces orthogonal dimensions that maximize the variance explained by each. In the nonlinear model discussed below, the reduction used uniform manifold approximation and projection, which aims to preserve local information over global information. And in the final linear model, another singular value decomposition was used, this time rotated to place the effect of `Day` on the x-axis and the highest remaining variance on the y-axis.

Networks were visualized using network graphs where nodes correspond to the qualitative codes and edges reflect the relative frequency of co-occurrence between two codes. In the final linear model, these networks were compared using network difference graphs that illustrate differences between pairs of clusters by subtracting the weight of each connection in one cluster from the corresponding connection of the other. To improve legibility and parsimony of the resulting difference plots, Pearson correlations were run between the grouping variable and each connection, and connections with correlations below 30% were omitted.

To further test for differences between pairs of clusters, I applied a Mann-Whitney test to the location of the points in the final projected ENA space for units in each cluster, with a Bonferroni correction.

3.4 Nonlinear ENA

The ENA algorithm is a three step process. First, ENA represents qualitative data as a high dimensional space that models the connections between qualitative codes [18]. Second, ENA uses multidimensional scaling to reduce the dimensionality of that space while highlighting features of interest [18]. And third, ENA projects a network representation onto that scaled space as a way to illustrate the dynamics of those features [18]. Existing multidimensional scaling algorithms used by ENA have been linear, such as Means Rotation and Principle Component Analysis [18]. Linear dimensional reduction retains global information and is useful for hypothesis testing [20]. However, linear dynamics lead to stories told structurally around two points: a control vs. a treatment, a before vs. an after, or so on. Such stories fail to model the richness of transitions as experienced, as discussed in the results below. Therefore, my departure from existing ENA is to use a nonlinear multidimensional scaling algorithm instead. Nonlinear dimension reduction retains local information and is useful for hypothesis generation [20], and nonlinear dynamics, as demonstrated in the results below, captured the local ebbs and flows of a transition as experienced.

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) has been used in the context of ENA before, DBSCAN has been used with Uniform Manifold Approximation and Projection (UMAP) outside of QE for temporal data visualization, and empirically UMAP has seen success in retaining insightful global structures [21, 22]. Therefore, I select UMAP and DBSCAN as my nonlinear dimension reduction and clustering algorithms for this demonstration. UMAP was used to reduce the dimensionality of a matrix where each column corresponded to a single ENA unit, and each row corresponded to a different ENA connection, with one row added to represent the normalized `Day` number. This results in a model that can be used to project the high dimensional space to a 2-dimensional plane and project additional points into that plane. Density-based clusters of similar "types" of days within that plane were then detected and labeled using DBSCAN.

To visualize UMAP and DBSCAN results, units were initially visualized color-coded on a spectrum from red (early days) to green (middle days) to blue (later days), and then subsequently color-coded based on cluster number. Networks were then projected into the space drawing on the network projection algorithm already used by ENA: In existing ENA visualization techniques, network connections are drawn as straight lines, such that the "elbow" of the line occurs at its mid point, and units are as near as possible to the "center of mass" of their respective networks' elbows [18]. A consequence of this is, if a unit has *only* connections between two given codes, then one expects that unit to be positioned exactly on that connection's elbow, though in practice this is approximate. So in deciding how to visualize networks in the UMAP space, I retained that intuition. Hypothetical units were constructed for each pair of codes such that that "unit" has only connections between that pair of codes and a missing value for its `Day` number. These network "units" were then projected into the UMAP plane and used as positions for connection elbows. The consequence of this is that units are visualized in the "neighborhoods of the elbows" for which they are likely to have connections. Nodes were then positioned such that, *were* the lines straight, units would be as close as possible to their networks' centers of mass. This is the same method used in ENA, and it has three consequences. One, nodes tend to be positioned legibly. Two, nodes positioned towards the edges of the the plot are those that one should expect most linearly discriminate the global structure modeled by the plot. Three, specific to the nonlinear context here, one should expect clusters positioned near a given node to have many, various connections to that node.

4 Results

4.1 Existing Methods

The initial ENA model (Figure 1) had a co-registration Pearson correlation of 94% along the x-axis and 92% along the y-axis, indicating a strong goodness of fit between the visualization and the original model. The x-axis captures the difference between (left) days that made connections to `Happy` vs. (right) those that made connections to `SkippedDose`. The y-axis captures the difference between (bottom) days that connected `Happy`, `NonHappy`, and `Sweets` vs. (top) those that connected `REFLECT`, `BODY`, and `LEARN`.

In other words, the x-axis appears to model time, as early in the HRT process I was feeling doubts and skipped doses some days, and later, once I began to stick with it, I was happier more often. And the y-axis appears to model a difference between introspective days vs. days on which I was anxious and consumed caffeine: An accident of being stuck in my house during the pandemic, I ran out of caffeinated drinks, at which point I realized I craved drinks like Red Bull (`Sweets`) when I was anxious (`NonHappy`), which compounded the anxiety.

These results are affirming! It warms my heart to see `Happy` placed in systematic contrast to `SkippedDose`. However, there are three immediate qualitative problems. One, this does not tell a rich story: "Happiness," no matter how morally relevant, is a thin concept. Two, what story it does tell too readily supports deficit narratives: The story is reduced to two poles, an ostensible "before" and "after," around which one can read my transition as a movement out of "damage" without any indication of where my own hopes might factor into that story. Three, it gets the story wrong: Skipping doses did not happen at the beginning of the story, tracking doses did, and the event that most brought about a structural break in my networks is missing:

In the first few months on HRT, I repeatedly started and stopped taking my prescriptions, a vicious cycle between (a) dysphoria and desire prompting me to start and (b) doubt prompting me to stop. Then, I ran low on pills. I ran out of refills. My doctor retired. Because I had taken these breaks, I messed up the timing we had worked out at my initial consult, and I was unable to get my prescriptions filled by another university doctor until nearer the Fall semester when my student status would resume. When things picked up around July and August, I had doubts again. However, this time I had several months of daily notes to reflect on. Re-reading these, I noticed that each time I had doubts was in the days leading up to picking up refills from the pharmacy. In my anxious mind, I would have to "prove" to the pharmacist that I deserved my prescription. I would have to "prove" it to my family, my friends, co-workers, students. And so I would stop. I communicated this to my new doctor at our first meeting. She sent me an email shortly after with a simple solution: She would put me down for a three-month dose so I would have to go to the pharmacist less often. It was this event, more than any other, that allowed me to find stability in my transition and move towards the goals I set for myself on my very first day: "I value happiness, passing, and understanding."

The existing linear approaches to ENA fail to capture these tensions between doubt and desire. The proposed nonlinear extension, on the other hand, elucidates it.

4.2 Nonlinear ENA

In the nonlinear projection (Figure 2), `Happy`, `DoseTracking`, and `SkippedDoses` are placed around the edges, and the remaining nodes towards the center. The dose-related codes appear in opposition to happiness, as though creating a Y-shaped plot. Visually, the red to blue shift suggests an "arrow" of time that moves from the bottom left, where I tracked the doses I was taking down to the minute (information that I did not need but felt the need to keep anyway); over to the bottom right where I skipped doses; then back to the left, now a bit further up; and eventually continuing up and left towards `Happy`.

DBSCAN detected six clusters, numbered in order from earliest first-occurring unit to latest first-occurring unit. For brevity, I omit clusters 3 and 4 from discussion here: they are small; they are qualitatively less insightful than the others; and a discussion of clusters 1, 2, 5, and 6 suffices to demonstrate the method.

Between February 14th, 2020 and August 23rd, 2020, clusters 1 and 2 co-occurred. During that period I alternated between "1-type" days and "2-type" days, with a longer 2-type period over the Summer. Then, until November 14th, 2020, cluster 1 and cluster 5 co-occurred, with 1-type days decreasing in frequency and 5-type days increasing. Then, until the end of the year under study, cluster 5 and cluster 6 similarly co-occurred, with 5-type decreasing and 6-type increasing.

Visually, cluster 1 is located in the neighborhood of connections to `Dose Tracking`. Cluster 2 is similarly located near `Skipped Dose` and cluster 5 near `Happy`. Cluster 6 is located in the neighborhood of the connection between `Happy` and `PROGRESS`. Notice too that cluster 1 has a "chunk" missing, corresponding to the Summer 2-type days when I was unable to refill my prescriptions.

4.3 Quantitative Results

All statistical tests reported below are adjusted with a Bonferroni correction of $\frac{\alpha}{4}$.

Table 2 gives summary statistics of code counts within clusters 1, 2, 5, and 6. Using a χ^2 test, I reject the null hypothesis in favor of the alternative that there is some relationship between these clusters and the counted codes at the $\alpha = 0.05$ level ($\chi^2 = 349.482$, $p < 0.0001$).

The final ENA model (Figure 1) was limited to only units in clusters 1, 2, 5, and 6 and rotated to show the effect of the `Day` number along the x-axis. This model had a co-registration Pearson correlation of 98% along the x-axis and 91% along the y-axis, indicating a strong goodness of fit between the visualization and the original model. Along the y-axis, a Mann-Whitney test showed that cluster 1 ($Md_1 = 0.17$, $N_1 = 53$) was statistically different at the $\alpha = 0.05$ level from cluster 2 ($Md_2 = -0.19$, $N_2 = 36$, $p < 0.0001$, $U = 1789$). Similarly, along the x-axis cluster 1 ($Md_1 = -0.29$) was statistically different from cluster 5 ($Md_5 = 0.19$, $N_5 = 69$, $p < 0.0001$, $U = 3654$), and cluster 5 was statistically different from cluster 6 ($Md_6 = 0.44$, $N_6 = 12$, $p < 0.012$, $U = 224$).

Figure 2 shows the connections most prominent in each of those clusters. As was suggested by the placement of the nodes, cluster 1 was dominated by connections to `DoseTracking`, had connections to and between the introspective codes, and had few connections to `Happy` or `Progress`. Cluster 2 had connections between `SkippedDose`, `Reflect`, and `BODY`, with few other connections. Cluster 5 was dominated by connections to `Happy`, with many connections to and between the introspective codes, connections to `PROGRESS`, and almost no connections to `DoseTracking` or `SkippedDose`. Cluster 6 had almost only connections between `Happy` and `PROGRESS`.

Figure 1 shows the difference between these clusters in their time order: cluster 1 vs. cluster 2, cluster 1 vs. cluster 5, and cluster 5 vs. cluster 6. First, among other possible differences, cluster 1 had more connections to `DoseTracking` and cluster 2 had more connections to `SkippedDose`. Cluster 2 also had a few more connections between `SkippedDose` and `Happy`: giving up can bring about its own ostensible form of happiness. Second, and similarly, cluster 1 had more connections to `DoseTracking` and cluster 5 had more connections to `Happy`, most notably the connection with `PROGRESS`. Finally, among other possible differences, cluster 6 had relatively more connections between `Happy` and `PROGRESS` than cluster 5.

Table 2. Code counts for clusters 1, 2, 5, and 6.

Cluster	BODY	DoseTracking	Happy	LEARN	NonHappy	PROGRESS	REFLECT	SkippedDose	Sweets
#1	37	39	3	18	28	5	27	0	22
#2	23	0	7	6	6	4	21	36	12
#5	37	1	60	20	26	40	39	0	32
#6	0	0	12	6	1	11	0	0	0

4.4 Qualitative Description

To better understand the difference between clusters 1, 2, 5, and 6, I focus my attention to `PROGRESS` in connection to the three dominating codes, `Happy`, `DoseTracking`, and `SkippedDose`.

The only occurrence of `PROGRESS` during the earlier half of cluster 1 was on April 27th, 2020. At this point, I had started and stopped HRT a few times. That day, I wrote:

> [1] 9:10p in my last note [this date], I was also thinking, from that dream, that I am tired of picking myself apart to get at the kinds of womanhood that are important to me. can't I say, I want to be a woman, and that be enough?
> [2] e -s
> [3] 10p did i want to be shirley temple as a little kid?

In the first line, I am marking the time, to the minute, for this reflection, and on the second line I am marking that I took an Estradiol and not a Spironolactone at that time ("e -s"). On the final line, about 20 minutes after the Estradiol would have finished dissolving under my tongue and when I would have been getting ready for bed, I wrote a quick reflective question about my childhood: I recalled being into Shirley Temple when I was young and living at my grandmother's, and I wanted to note the memory so that I might reflect on it more later. But

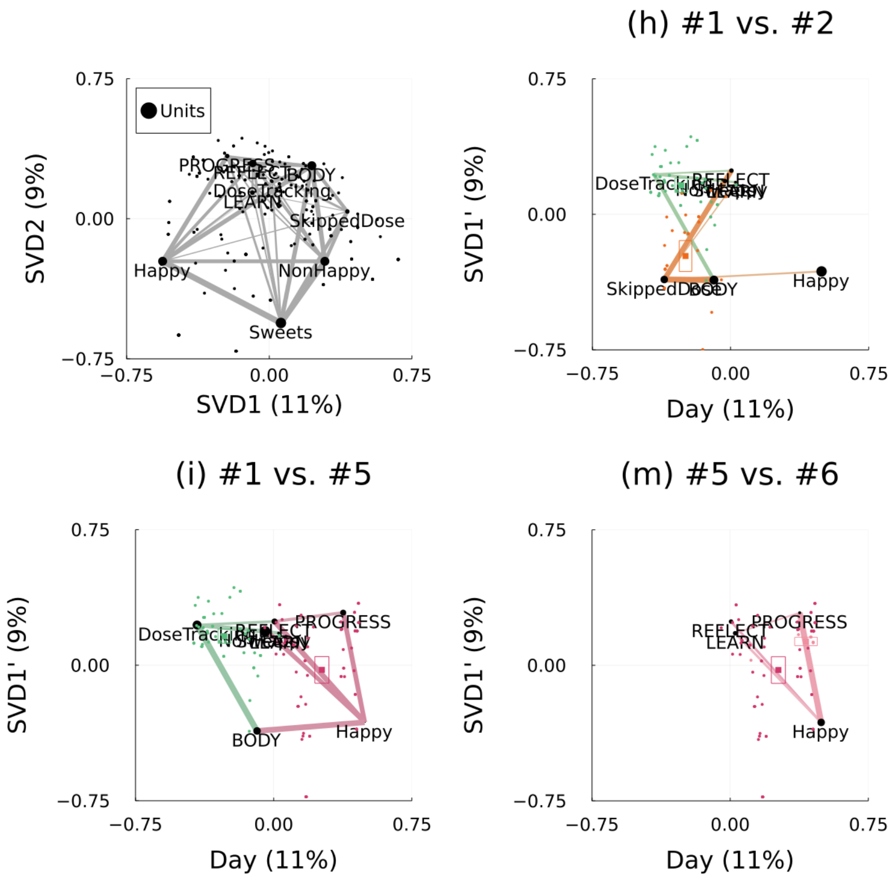

Fig. 1. Linear results. (top left) ENA plot with SVD rotation. (remaining) Difference between group-wise networks in a linear projection showing the effect of `Day` along the x-axis. Group means and confidence intervals are shown by squares and the boxes around them. Also note that groups did not exist *a priori* and were detected through the non-linear process.

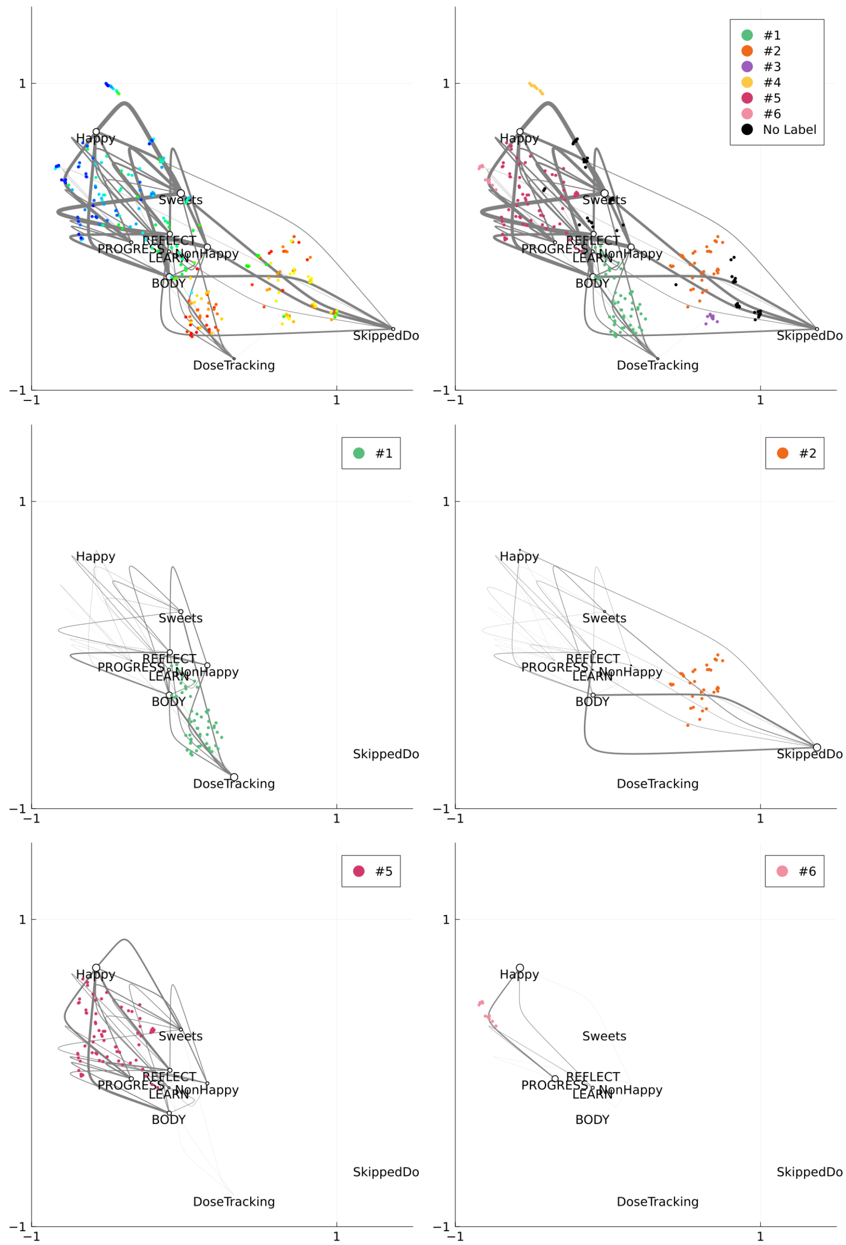

Fig. 2. Non-linear results. (top left) Spectral color coding to show movement of time, from red to green to blue. (top right) Cluster-wise color coding. (remaining) Group-wise networks in the UMAP projection.

the most important part of this note was at the end of the first line: I was tired of all the ways I had been seeking "proof" during those first few months and so I, probably linguistically influenced by "ain't I a woman," wrote my first affirmation during the year under study, here as a rhetorical question.

Daily notes were rare during cluster 2. Most of the data I have for that period comes from my "checkbox" app, which was a quick and habitual end to my day after working out and before going to bed each night. But as the Fall semester was starting up, and when I had, once again, started and stopped HRT, I wrote:

> [1] when i stopped taking hrt both times and my breast development reduced it hurt it felt like coming home to realize your dog had died
> [2] i felt strong, powerful last night, doing yoga. like korra. lots of warrior 1 and 2

In the first line, I am trying to capture a specific kind of sadness, describing for the first time in my notes the relationship between concrete changes to my body and my sense of self. But this description of loss should be read with a tension of happiness to it: This was a clear, recent, and analytic moment that I could point to to abate my anxious mind. Holding onto that, I was able to let go of some worries, and I wrote an affirmation on the second line, relating myself to Korra, the queer and female protagonist of the cartoon series *The Legend of Korra*.

That act of affirmation was a rare bit of progress during this time period. It is easier to see my state of mind during cluster 2 by seeing the notes I wrote in cluster 1 right before a string of 2-type days. On May 4th, 2020, I logged that I had taken Estradiol without Spironolactone at 8:05am. At 3:40pm, I reflected on my relationship with gender and with cognitive behavior therapy. And at 5:15pm, I recounted the first time I had passed as a woman in public during the year under study: I was called "ma'am" while standing in line at Menards. But then weeks later, I wrote comments such as "thinking about stopping hrt" and "i am leaning towards stopping hormones."

Then September 15th, 2020, because I had talked with my doctor about how my doubts surfaced every time I was getting ready to visit the pharmacist, she sent me the message, "If you would be interested, I could put in 3-month supply worth of the medications for you to pick up at once. This would mean less trips to the pharmacy, which might be helpful for you." During the months that followed, I stopped tracking my doses. I simply took them. I passed more and more often in public as I gained the confidence to wear more female-coded clothes. And I wrote affirmations more often, such as "I'm not late onset I'm late opportunity," responding to an imagined critic that might criticize me for my later in life transition.

Throughout cluster 5, I had taken many steps towards building a stock of new clothing, new glasses, signing up for a make-up subscription service, and so on. The emotional and material capital I had gained during cluster 5 enabled me to start coming out to more friends, then co-workers, and eventually, in cluster 6, to my students and my hair stylist. All throughout my first year on HRT, it was these moments of incremental and concrete progress, enabled by repeat analytic reflection and support from my care providers, that allowed me to feel more comfortable as myself around other people and to write the following, towards the end of the year under study and days after the previous ICQE conference:

[1] got called maam on the phone when talking to [my dentist]
[2] ive been feeling really good about myself lately
[3] the haircut really helps [heart emoji]

5 Discussion

In this paper, I asked, *How can QE be used to tell a temporal story?*. To answer this, I have demonstrated Nonlinear ENA, an extension to existing QE methods that incorporates a nonlinear projection algorithm (in this example UMAP) and a clustering algorithm (in this example DBSCAN). This extension provides several affordances when working with temporal data. I illustrated this method using analytic autoethnographic data collected during my first year of feminizing hormone replacement therapy.

First, these techniques allowed me to make systematic decisions about how to relate units with similar units nearby in time when I had no *a priori* structure. Grouping the days into weeks or months would have imposed an artificial structure, one that would not have aligned with the time period as experienced in the day-to-day. Nor would grouping the days into equal-sized units have captured the ebb and flow and sometimes back and forth between multiple "types" of days.

Second, it identified which of many qualitatively meaningful moments actually incurred a structural break and provided a grounded and saturated structure by which to organize my narrative. Yes, I structured my account around the importance of an email from my doctor, but in my initial reflections before running the UMAP analysis, I was less informed about whether other personally important moments would have also incurred structural breaks: Coming out to my advisor, choosing a new name, quitting caffeine, and so on.

Third, it neatly modeled nonlinear behavior and visualized the effect of a structural break on that nonlinear behavior. I was only able to escape the vicious cycle of starting and stopping HRT once my doctor changed my dose to a three-month supply.

Finally, these results were reflectively surprising, which promoted clearer theoretical thinking. To me, "coming out" was the end of the story originally. And while that may be true in literal time order, its theoretical insight was limited by its infrequency: Once I came out to everyone in my day-to-day life, there was no one left to come out to, so `Out` was structurally different from other low-level codes. Even in earlier iterations of the UMAP projections where `Out` was a node, `Happy` retained its dominant position. It was reflecting on this that I realized: The insight I was drawn towards wasn't about coming out in itself, but about the different forms that *progress* took on when in connection to each of the time periods.

Altogether, these affordances allowed me to tell a rich, informed, and desire-based story that I was unable to tell using existing QE methods. In future work, I hope to refine this technique for data with multiple participants and for use with continuous variables other than time.

References

1. Deutsch, M.: Overview of feminizing hormone therapy, https://transcare.ucsf.edu/guidelines/feminizing-hormone-therapy. Last accessed 15 April 2021.
2. Antony, A.: Tacit Knowledge and Analytic Autoethnography: Methodological Reflections on the Sociological Translation of Self-Experience. Revealing Tacit Knowledge: Embodiment and Explication. Transcript, Verlog. 139–167 (2015).
3. Knowles, M., Shaffer, D. W. (2021) Hierarchical Epistemic Network Analysis. In: Ruis A.R., Lee S.B. (eds) Second International Conference on Quantitative Ethnography: CONFERENCE PROCEEDINGS SUPPLEMENT. ICQE 2021. The International Society for Quantitative Ethnography.
4. McDonald, N. et al: Reliability and Inter-rater Reliability in Qualitative Research: Norms and Guidelines for CSCW and HCI Practice. Proceedings of the ACM on Human-Computer Interaction (2019).
5. Vryan, K. D.: Expanding Analytic Autoethnography and Enhancing its Potential. Journal of Contemporary Ethnography **35**(4), 405–409 (2006).
6. Astor, M.: Asa Hutchinson, G.O.P. Governor of Arkansas, Vetoes Anti-Transgender Bill. New York Times (5 April 2021).
7. Brown, N. M.: Methodological Cyborg as Black Feminist Technology: Constructing the Social Self Using Computational Digital Autoethnography and Social Media. Cultural Studies & Critical Methodologies **19**(1), 55–67 (2019).
8. Anderson, L. A.: Analytic Autoethnography. Journal of Contemporary Ethnography **35**(4), 373–395 (2006).
9. Tuck, E.: Suspending Damage: A Letter to Communities. Harvard Educational Review **79**(3), 409–428 (2009).
10. Meleis, A. I. et al: Experiencing Transitions: An Emerging Middle-Range Theory. Advances in Nursing Science **23**(1), 12–28 (2000).
11. Levitt, H. M., Ippolito, M. R.: Being Transgender: The Experience of Transgender Identity Development. Journal of Homosexuality **61**, 1727–1758 (2014).
12. Nehushtan, H.: Embodying Normalcy: Women Exiting Sex Work and the Boundaries of Transformation. Qualitative Sociology **43**, 565–581 (2020).
13. Ohsaka, A., Ohsima, J.: Socio-semantic Network Analysis of Knowledge-Creation Discourse on a Real-Time Scale. ICQE, CCIS **1312**, 170–184 (2021).
14. Wooldridge, A. R., Haefli, R.: Using Epistemic Network Analysis to Explore Outcomes of Care Transitions. ICQE, CCIS **1112**, 245–256 (2019).
15. Emerson, R. et al: Processing Fieldnotes: Coding and Memoing. Writing Ethnographic Fieldnotes. Chicago (2011).
16. Shaffer, D. W., Ruis, A. R.: How We Code. ICQE, CCIS **1312**, 62–77 (2021).
17. Hughes, S. A, Pennington, J. L.: Autoethnography: Process, Product, and Possibility for Critical Social Research. SAGE Publications (2017).
18. Shaffer, D. W.: Quantitative Ethnography. Cathcart, Madison (2017).
19. Siebert-Evenstone, A. et al: In search of conversational grain size: modelling semantic structure using moving stanza windows. J. Learn. Analytics **4**(3), 123–139 (2017).

20. Nguyen, L.H. and Holmes, S. Ten quick tips for effective dimensionality reduction. PLoS Comput Biol **15**(6) (2019).
21. Ali, M. et al: TimeCluster: dimension reduction applied to temporal data for visual analytics. The Visual Computer **35**, 1013–1026 (2019).
22. Nguyen, H. et al: Establishing Trustworthiness Through Algorithmic Approaches to Qualitative Research. ICQE, CCIS **1312**, 47–61 (2021).