Gender is Complex: pulling the Laplacian EigenGender from relationship graphs

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Abstract

What is gender? Sociologists, biologists, and philosophers have been debating this question for centuries. As computer scientists, we know better. We do recognize that gender is complex and thus propose to model it with complex numbers.

In this paper, we present a novel method for extracting the latent gender vector of individuals from romantic relationship graphs. We demonstrate the effectiveness of our Big Data Structure Modeling method, EGG🐣BREAKER, on the internet famous Jefferson High dataset. For each person in the dataset, EGG🐣BREAKER produces LEGs (Laplacian eigengenders), 4D vectors that predict the structure of the relationship graph with 94% accuracy.

1 Introduction

We ignore all prior work. Our theory of gender is based on freshman linear algebra and Blanchardian psychoanalysis.

We will start from first principles (math presented without justification). Suppose at least one person exists. The **Gender Direction (GD)** g of that person is an element of the **Human Gender Hilbert space (HGH)** H equipped with an **attraction kernel** $\alpha : H \times H \to R$ which maps pairs of humans' genders to the unnormalized log probability they are attracted. It is obvious the kernel will be symmetric (in an ideal world). Research has shown that people are attracted to those similar to themselves (the kernel is positive semidefinite) and attraction can be predicted by a linear model (though crudely) [Spr+94] [Aro+89].

One natural candidate for the attraction kernel is the inner product of the HGH κ. By the Cauchy-Schwartz inequality, this choice leads to a narcissism problem: any person would be most attracted to a multiple of themselves. This prediction does not match the stated preference of most people [iex]. Where did our modelling go wrong?

We will turn to "transsexual typology" for an answer. In [Bla89], Ray Blanchard claims that transgender individuals can be classified into just two categories: homosexual and heterosexual. *Autogynephylia*, the term proposed for males experiencing gender dysphoria due to being "sexually oriented toward the thought or image of themselves as women", is a replacement for the earlier *automonosexualism*. In its original defintion, the latter meant "pathological narcissism in which the individual is excited by his own body as it is". This is starkly similar to our characterization of the gender cosine similarity attraction kernel, where a person likes themselves most. Blanchard holds that automonosexualism is caused by heterosexual attraction to an imagined partner. But according to Fruedian psychoanalysis [Fre14], the opposite is true: narcissism is primary and develops into attraction.

Motivated by this discovery, we will rework the attraction kernel to fit the real world. We have proven that heterosexuality is a result of narcissism. We can easily account for this with a **HAK (heterosexual attraction kernel)**: $\frac{\langle x, -y\rangle}{|x|||y||}$. An astute reader will notice that we just flipped the signs of one of the variables and that even though this HAK allows for an infinite number of genders, it cannot account for homosexuality. We can easily account for this fact using a more general **human romantic translation (HRT)** matrix. is an orthonormal transformation that turns gender vectors into those of a preferred gender. With HRT, the kernel becomes $\frac{\langle x, \mathrm{HRT}y\rangle}{|x|||y||}$.

Because HRT is orthonormal, we can transform all GD vectors by its Cholesky decomposition to produce **eigengender** vectors. In eigengenderspace, the attraction kernel is simply the cosine similarity again. Note that eigengender can be complex: if the HRT is equal to the number -1 as in the HAK, all components of the GD will be multiplied by i.

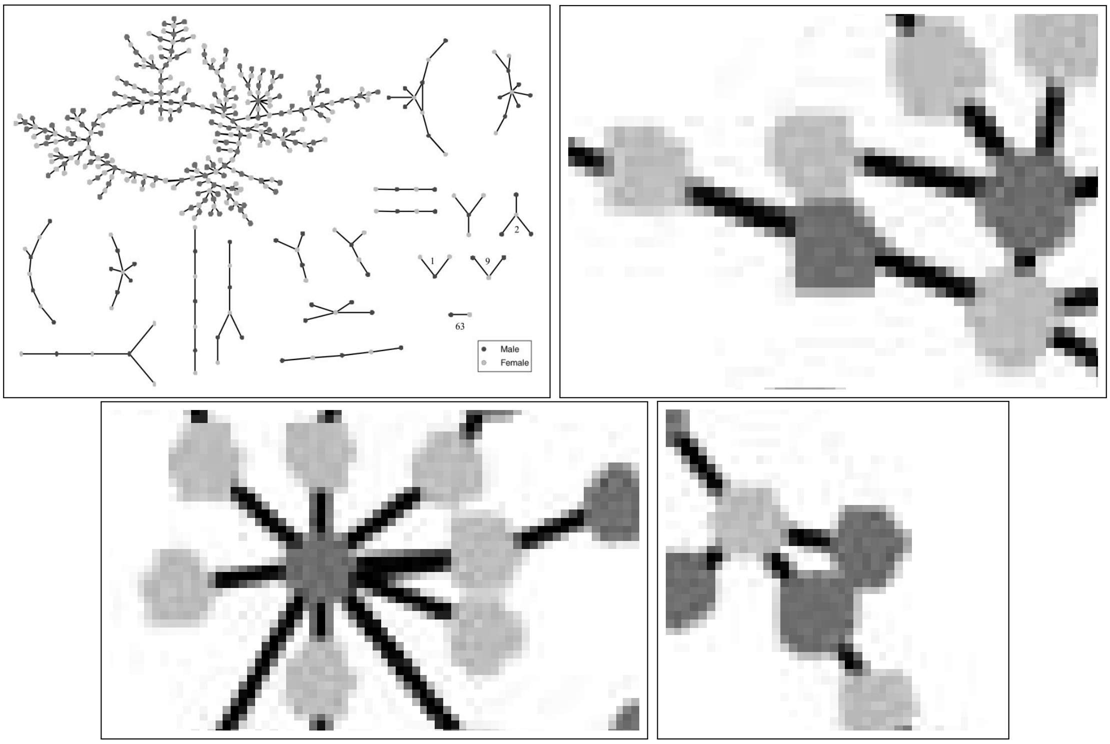

Figure 1: The Jefferson High dataset and its issues

2 Data

We proved from first principles that gender is a complex vector. We will apply the only useful tool other than first principles thinking: machine learning. Because eigengender is determined up to an orthonormal transformation by the gender attraction kernel, we can apply Yoneda Lemma or something to say that we can predict it from observations of romantic attraction.

[BMS04] is the only public dataset we could obtain in an ethical way.[1] The dataset looks real despite slander from anonymous Twitter users.[citation needed] The only concern we have is connectivity. We need diverse interactions to extract non-trivial and interesting (complex) eigengenders, but the graph is so sparse it is planar and there are only two gay couples.[2] But the planarity is also a blessing as it means we can parse it using computer vision.

Actually, we cannot. The figure is too blurry and contains ambiguous links (see fig. 1). The author painstakingly traced the graph in Krita 4.1.7 [Dev20] to be more pixelated and easier to parse (fig. 2). We extract subjects and links between them using connected components (fig. 2b).[3]

3 Methods

In the previous section, we mentioned that it should be possible to predict gender from observations. As we explained, the problem of predicting eigengenders is ill-posed even given a set of all possible interactions. But, when dealing with real data, not all possible links are sampled. This necessitates an approximation.

Recall that the attraction kernel outputs unnormalized log probabilities. The set of eigengenders we choose will be the one with the highest likelihood of producing the observed attraction kernel. Similarly to `word2vec` [Mik+13], this is a matrix factorization problem $XX^T \approx \alpha$.

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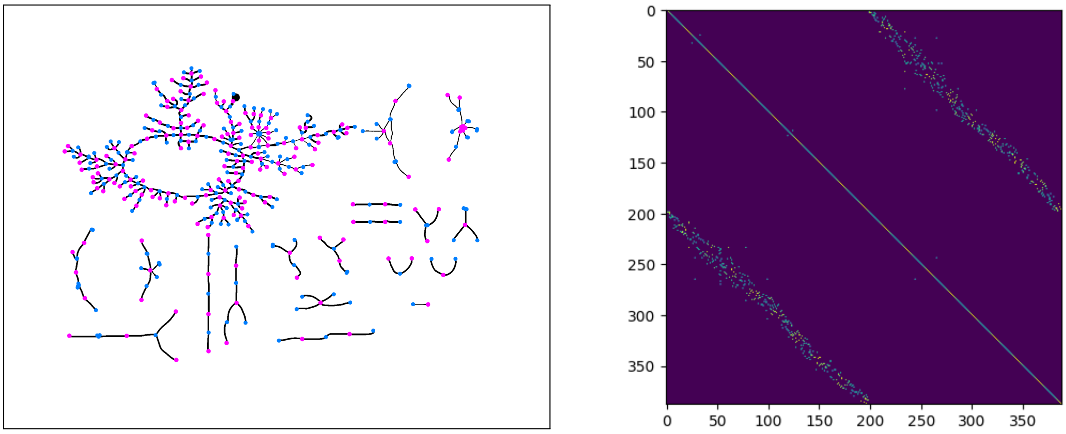
[1] We failed to get access to its source, Add Health [HU22] due to time constraints.

[2] In an old Reddit comment [BMU], an author says that some gay couples may have been excluded from the dataset. The only couples affected are the diatomic polycules, which are all equivalent and have the same predicted predicted gender regardless of ground truth.[21]

[21] This is *not* because the author was too lazy to duplicate the same structure 63 times.

[3] We will not be releasing the parsed traced data because you can just screenshot it. (We also made mistakes when tracing and are afraid of being called out)



(a) Our glorious traced dataset

(b) Parsed dataset adjacency matrix

Figure 2: Parsing the dataset through tracing. Notice the little gay dots near the diagonal.

3.1 Overview of the algorithm

In this subsection, we will break down the algorithm we use to find a matrix factorization, titled EigenGender Generation Based on Romantic Experience Adjacency Kernel with Elementwise Reweighting (EGG🐣BREAKER).

Gender will be represented as a $\mathbb{C}^d$ vector for each person. The magnitude for all d complex components is shared. [eigenvalues of orthonormal matrix have the same magnitude]. We will compute an approximation of the adjacency matrix by computing the real part[4] of the complex inner product of the eigengender matrix with itself. As an approximation of Bayesian (maximum likelihood) inference[5], we compute binary cross entropy and equalize the weighting of the two classes (attracted/not attracted) per person. This class reweighting is necessary because the data sample is sparse and we must focus on the observed links, just as in real life.

We optimize the loss of the eigengender vectors on a full batch of the dataset using the Adam optimizer with a learning rate of 0.5. We use 500 iterations for all of our experiments.

4 Results

4.1 Evaluations

We evaluate the trained network on its accuracy at predicting the presence of relationships in the data. We compute accuracy using the eigengenders' predicted probabilities and not the top-1 prediction. We considered evaluated the accuracy with reweighting similar to what we used for the loss, but found no siginicant difference (fig. 3). We report accuracy over 4 runs because we're poor.

Our final eigengender-based model uses 2 complex numbers with shared magnitude per person. We considered some changes to this formula:

1. using ”quaternions” (normalizing the whole complex vector to have magnitude 1);
2. not normalizing the complex components to have the same magnitude;
   - storing gender in two separate vectors instead of one, breaking symmetry.
     - using real numbers for the vectors (with twice the dimensionality), breaking puns about complex numbers in addition. Disqualified for the latter.

The results are as follows:

[4] So it's symmetric.
[5] trust me bro

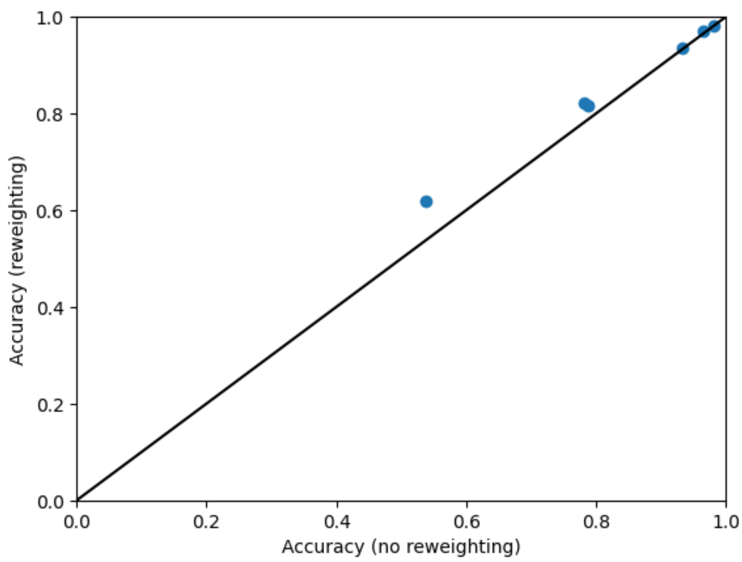


Figure 3: Accuracy evaluation with and without reweighting

Method	Accuracy
Baseline	$0.92 \pm \mathbf{0.02}$
"Quaternion"	0.522 ± 0.00
No norm	$\mathbf{0.944} \pm 0.00$
Separate components	0.941 ± 0.00
Real (disqualified)	0.948 ± 0.00

What is the optimal number of components? We can use the eye-elbow method[6] and brute force search to find out. Unsurprisingly, the answer turns out to be 2 (fig. 4).

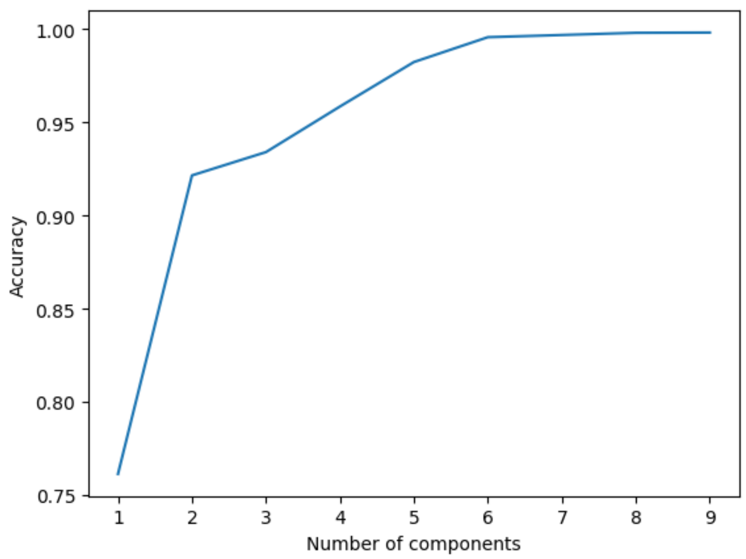


Figure 4: Eye-elbow chart for calibrating gender dimensionality

4.2 Visualizations

What does eigengender look like? Since we have a planar visualization of the relationship graph handy, we can attempt to answer this question. Thanks to our shared-magnitude parametrization, we

[6]Application of the elbow method by eye.

can ignore gender magnitude as it only scales up attraction and focus on gender phase. Specifically, we can overlay the imaginary component of the logarithm of the eigengender in shades of purple (fig. 5).[7] We standardize the elements of the gender phase vectors to lie in $[0, 1]$.

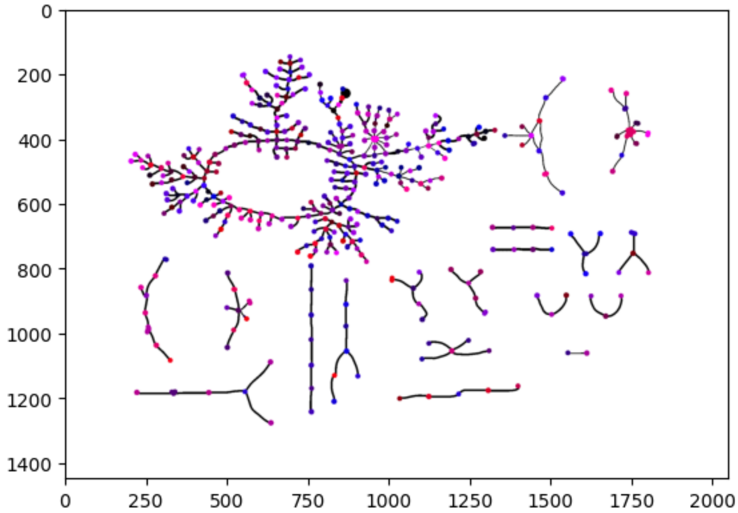


Figure 5: Naive eigengender phase visualization

In our setup, gender is a local variable; because the data graph is planar and the loss depends only on interactions with neighbors, a gender only makes sense in the context of a neighborhood.[8] We may try to correct for this effect by subtracting the average gender phase of neighbors from the gender vector of each node. In effect, we are computing the graph Laplacian, earning us the "L" in "Laplacian Eigengender" fig. 6. To our disappointment, the end result looks exactly the same.[9][10]

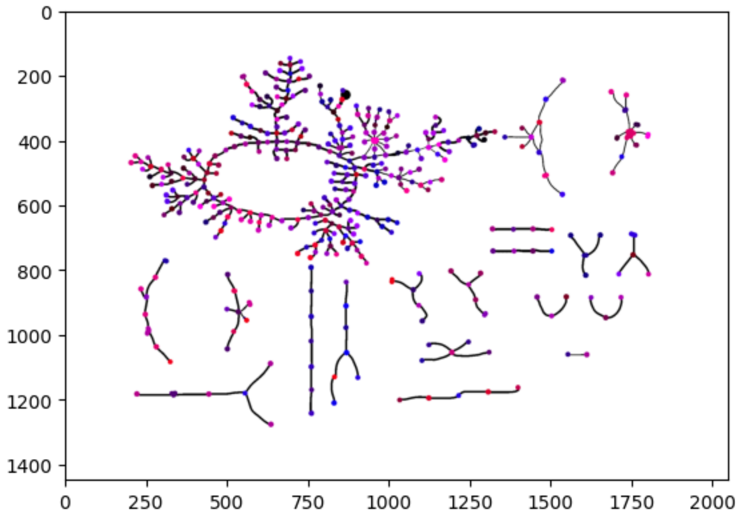


Figure 6: Laplacian eigengender visualization

As a sanity check and baseline, we computed the graph Laplacian eigenvectors. The hope is that this factorization will discover something similar to gender without explicit training. They are completely meaningless - either constant or with genders assigned only to a few nodes (fig. 7).

[7] Red/blue in RGB.

[8] We propose to call this "roommate effect".

[9] No we were not too lazy to generate a second image. The graphs are just very similar.

[10] "L" indeed.

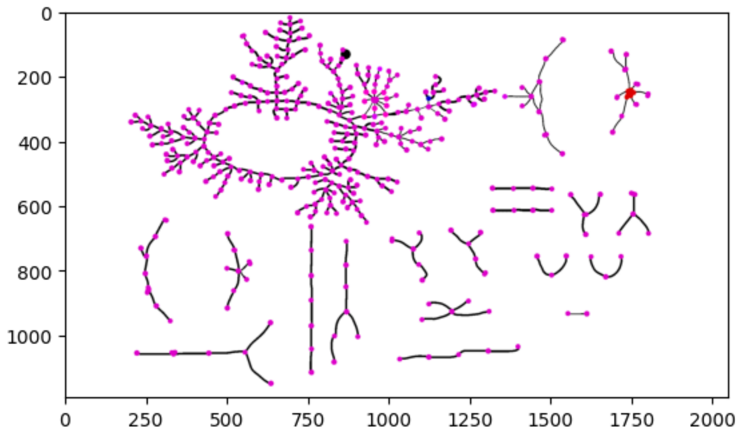


Figure 7: Top-3 graph Fourier transform genders

4.3 Geometry of 3+1D eigengenderspace

Confusingly, the magnitude appears to only be a minor factor contributing to accuracy – there is a mere 4% drop in accuracy from tying magnitude for two complex numbers. If two complex numbers always have the same magnitude, we can visualize isosurfaces with respect to this magnitude as donuts. What if we consider the entire 3D manifold of such complex numbers? Can we embed it into 3D space so mortals can comprehend it?

We generate 4096 random normally distributed vectors of the form described above and compute a 3-component UMAP on them. The results do not[11] make any more sense, but they look pretty (fig. 8).

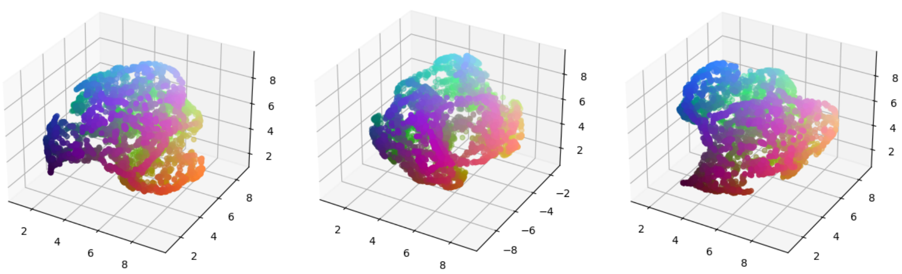


Figure 8: Confusing gender donut

When we computed a 2D embedding, the results shocked us. Staring back at us was none other than internet frog Pepe.

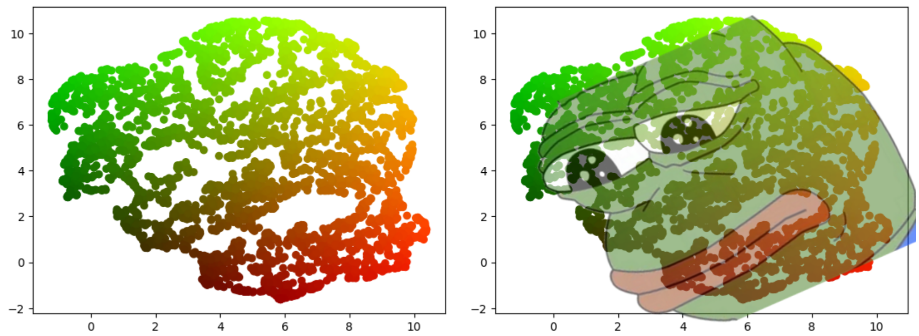


Figure 9: Pepe?!

We leave investigation of this phenomenon to future work.

[11] Pun intended.

5 Discussion

> We have shown that the Laplacian EigenGender is a powerful tool for understanding the structure of relationship graphs.
>
> *GitHub Copilot*
> *maybe*

The initial results of applying EGG🐣BREAKER are promising, but the inevitable confirmation our theory is impeded by the sparsity of the dataset. In the future, we should use a bigger, more connected dataset that better represents gender variance and contains less local interactions to allow for comparison between genders in far away neighborhoods. It is possible that `manifold.love`[Mar23] could mature to become this source of data, but we would not bet on it. Additionally, this paper was hyperfocused on romance; we could extend HRT gender theory to other gendered interactions such as liking memes or putting badges on backpacks.

Our setup is related to holographic reduced representations [Kle+22] because complex numbers and dot products. It is possible that the resonator network algorithm can be applied to our problem. We preemptively name this technique "HRT-RN" (HRT matrix-less factoring using Resonator Networks) (Holographic Reduced Typology from Resonator Networks).

6 Acknowledgements

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