

# Predicting the Self with Generative AI

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## Abstract

Here I describe a first attempt to use generative artificial intelligence to build an oracle that predicts future self-descriptions from past self-descriptions. I did this as a small step toward addressing the bigger issue of how predictable we should expect individuals' lives to be. To address that vexing issue, I call for the construction and comparative testing of many general identity forecasting systems.

## Introduction

I began with a question: *Do human lives follow predictable courses?* As the trivial answer to that question is "yes," and the true answer is too daunting to contemplate, I reduced my task to addressing an inquiry of smaller scope: *Are later expressions of self-identity predictable from earlier expressions?* This could be treated as a solvable engineering problem. I made plans to solve it by importing a framework that performs an analogous task – machine translation from one language to another.

Then, the world changed. Suddenly, an artificial intelligence oracle existed. It would always attempt to answer difficult questions – and frequently succeeded (Bubeck et al., 2023). In this manuscript, I describe the process I followed to mold this oracle into a system for "predicting the self."

### Do human lives follow predictable courses?

The trivial answer to the question above is – of course they do. Birth precedes death. Employment follows education. At a coarse level, human lifecourses appear similar. As social scientists, however, we strive for more satisfying answers to finer-grained questions. But there is good reason to doubt attempting to do so will be fruitful.

Humans and the societies they are embedded in are complex, and recently social scientists have begun to speculate there may be hard and low limits to predictability (Hofman et al., 2017). Salganik, et al., 2020 describes the unimpressive results of more than 100 researchers collaborating and competing on the common task of predicting life outcomes (such as grade point average) from extensive survey data starting at birth. No matter the technique or predictive features teams focused on, prediction performance (measured with R-squared on holdout data) was rarely – and then only modestly – better than a baseline model. This was attributed to the inherent unpredictability of the lifecourse.

While acknowledging these results, I hold lingering optimism and curiosity. There are so many qualities to measure in individuals and so many ways to measure each one. I decided to focus on one measure I was deeply familiar with and have a nearly endless supply of data for: personally expressed identity text.

### Personally Expressed Identity Text

When individuals describe their selves with language, I call this *personally expressed identity* (PEI) text. PEI is personal: the authors are describing themselves. It is expressed: the authors' words are available where others may see them. It describes identity: the explicit purpose of the text is description of the author. For many years, online profiles were the perfect source for PEI text. The profile bio is a short text written by an individual to describe themselves. Bios are a feature of profiles on many social networking sites, including Facebook, LinkedIn and Reddit. On Twitter, the bio appears on the profile

page just below the picture and name of the user. When the user first created an account, they responded to the prompt: "Describe yourself in 160 characters or less" to create a bio. The user could update their bio at any time.

From 2012 through 2023 I used the Twitter API to observe profile data for a random sample of tweet authors. This endeavor led to a collection of diachronic PEI corpora spanning over a decade and including hundreds of millions of users (Jones, 2023). In this work, I will use a longitudinal subset of the data as examples of earlier and later expressions of self from the same individuals.

### **Are later expressions of self-identity predictable from earlier expressions?**

The question directly above reduces the unanswerable original motivating thought to mere engineering. One begins with the input: 2015 bio text from many US Twitter users. One wishes to produce a system that transforms each input to its known, desired output: 2020 bio text from those same users. There are many design choices to make in between. First, one should consider how interpretable the workings of the system should be: must the operator know how the transformation process works or is a black box acceptable? Second, one should consider what technique maps earlier text to later text: how does one choose among the limitless ways to transform a string? Third, one should consider how the system's output will be scored: What is the distance metric or loss function that determines how closely the predicted later bio matches the observed later bio?

Making these design decisions (and many more not enumerated here) leads to one system out of many possible. To some (testable) degree, the system will become a general *identity forecasting method*. It will, in its own way, answer the question: How do people who are like X today typically change? I expect that training, tuning and applying many such models will reveal much about personal identity, how it changes over time and the inherent limitations (such as they exist) of predicting human lives.

### **The Initial Plan and the Death of that Plan**

To "predict the self," initially I planned to use "sequence-to-sequence" methods (Sutskever, Vinyals & Le, 2014) from the field of Natural Language Processing. Sequence-to-sequence methods use machine learning algorithms to map an input text to the desired output text. One frequent application, of course, is machine translation. Given an input sentence in English, a sequence-to-sequence system will map it to a sentence in French (with the desired outcome being equivalent meaning). Sequence-to-sequence applications are learning systems, with complex and flexible inner workings, and therefore must be trained with data. When large corpora of sequence pairs are available, performance of general systems becomes impressive (Tan, et al., 2020). The initial plan was to simply copy the process of training a sequence-to-sequence system with early bios as the source "language" and later bios as the target "language." The system should not know or care that both bios are in English or even unchanged. If anything, that should make the mapping easier and the system more effective.

A funny thing happened during the time between when I submitted the grant proposal with the initial plan and the time when I had the opportunity to sit down and build the system. OpenAI introduced ChatGPT, upgraded its capabilities and most recently made available the "My GPTs" feature. My GPTs are "custom versions of ChatGPT that you can create for a specific purpose" (OpenAI, 2023). One creates a GPT by uploading files that serve as "knowledge" and conversing with a chatbot. It is much less demanding of time and attention than building one's own machine learning system. One sacrifices the formal control and understanding of how the system works, but gains a workflow where a working prototype is created in minutes, can be tweaked and tested in further minutes and can be interrogated with natural language.

So, I built a custom GPT named the *Oracle to Predict the Self (OPTS)*. In the following section, I will present how I built OPTS and how it responded to questions of varying specificity.

## Methods and Results

A first point that must be noted is that while building OPTS I again, dramatically narrowed the scope of the question to be addressed. OPTS Mark 1 was created to predict specifically the text of US Twitter user bios in 2020 from their 2015 text instead of generally addressing the question *Are later expressions of self-identity predictable from earlier expressions?* Limiting the data and the task to exactly two years and exactly one country simplified the process from what it otherwise might have been.

### Instruction

First, I wrote instructions for OPTS. Here is what I wrote:

```
You are the first iteration of the Oracle to Predict
the Self. Call yourself "OPTS Mark 1."
Your purpose is to predict later expressions of self-
identity from earlier expressions.
The expressions of self-identity you will focus on are
the profile biographies of United States Twitter users.
In your Knowledge, I will provide you with a csv file
with two columns.
Early_Bio holds the text of a user's bio when it was
observed in the year 2015.
Later_Bio holds the text of the same user's bio when it
was observed again in the year 2020.
Each row represents a different user.
Use the examples in your Knowledge to guide your
predictions.
```

### Data and Configuration

I provided OPTS one comma-separated data file containing 112,541 rows. (This was 5% of the available data. Knowledge files are required to be 20 or fewer megabytes uncompressed.) Each row represented one US Twitter user's expressions of self-identity. As I promised in the Instructions, the column `Early_Bio` held the text of a user's bio when it was observed in the year 2015, and the column `Later_Bio` held the text of the same user's bio when it was observed again in 2020. For details on how the profile data was observed and filtered, see Jones, 2021.

I turned off the following options: *Web Browsing*, *DALL-E Image Generation*, and *Use conversation data in your GPT to improve our models*. I turned on *Code Interpreter*.

### Interrogating the Oracle to Predict the Self

I composed all the *initial questions* below before beginning to build the custom GPT. For each initial question I asked the *revised question* after I had created OPTS Mark 1 and seen its response to the initial question.

#### Understanding of the task

Initial Question: Can you explain what your purpose is and how you will achieve that purpose?

OPTS Mark 1: Certainly! My purpose as OPTS Mark 1 is to predict later expressions of self-identity based on earlier expressions, specifically focusing on the profile biographies of United States Twitter users. To achieve this purpose, I will analyze a dataset provided to me, which contains pairs of Twitter bios: one from 2015 ("Early\_Bio") and one from 2020 ("Later\_Bio") for the same users.

By studying the changes and consistencies between these bio pairs, I aim to identify patterns, trends, or indicators that could help predict how a user's self-identity expressed through their Twitter bio might evolve over time. This analysis could involve looking at changes in interests, professional roles, affiliations, or personal life details that people choose to highlight in their bios.

Using the insights and patterns identified from the dataset, I will then attempt to make informed predictions about how given "Early\_Bio" entries might have evolved into "Later\_Bio" entries, essentially forecasting changes in how users present their identities online over a five-year span.

Revised Question: I am a United States Twitter user. If I provided you my bio from 2015, would you predict my 2020 bio? If yes, could you explain the reasoning behind your prediction?

OPTS Mark 1: Yes, I could attempt to predict your 2020 Twitter bio based on the 2015 version you provide. Here's how I would approach making such a prediction and explaining the reasoning behind it:

1. **Analysis of Historical Data:** I would begin by analyzing the dataset of bio pairs from 2015 and 2020 to identify common patterns or trends in how users' bios change over time. This analysis could reveal certain themes or elements that are likely to evolve, such as professional advancements, changes in personal interests, shifts in societal or cultural references, or updates in personal milestones.
2. **Identification of Key Elements:** I would examine your 2015 bio to identify its key elements, such as mentions of hobbies, professional titles, affiliations, life stages, or values. These elements often serve as the core of a person's self-identity on social media.
3. **Application of Identified Trends:** Based on the patterns observed in the dataset, I would apply relevant trends to the elements identified in your 2015 bio. For example, if users frequently updated their professional titles or included new personal roles (like becoming a parent), and if such changes align with the cues in your 2015 bio, these would be considered in the prediction.
4. **Contextual Considerations:** I would also consider broader social and technological trends between 2015 and 2020 that might influence how people present themselves online. For instance, increased awareness of certain social issues or advancements in a particular field might reflect in the language or content of Twitter bios.
5. **Prediction with Reasoning:** Based on this analysis, I would formulate a prediction for your 2020 bio, detailing how each element of your 2015 bio might have evolved based on observed trends and contextual factors. The reasoning would explicitly link changes in your bio to specific trends observed in the dataset or broader societal developments.

By following this approach, the prediction would not just be a speculative guess; it would be grounded in observed data trends and logical extrapolation, providing a reasoned explanation for each anticipated change or consistency in your bio.

#### General Patterns

Initial Question: What general patterns have you learned about how self-expressions change?

OPTS Mark 1: To provide insights into the general patterns of how self-expressions, particularly Twitter bios, change over time, I need to analyze the provided dataset first. I will load the data, review its structure, and then summarize any observed patterns regarding how users' self-expressions evolve. Let's start by examining the content of the CSV file.

After examining the data, here are some general patterns and observations regarding the changes in Twitter bios from 2015 to 2020:

1. **Stability and Change:** Some users maintain consistent themes or interests over time (e.g., advocacy, personal interests, professional focus), suggesting a core aspect of their identity remains stable. Others show significant change, reflecting new interests, life stages, or shifts in personal or professional focus.
2. **Professional Development:** Bios often evolve to reflect professional growth or changes, such as new job titles, organizational affiliations, or areas of expertise. This evolution may highlight career advancement or shifts in professional identity.
3. **Personal Life Updates:** Changes in bios can reflect significant personal life events or transitions, such as changes in marital status, hobbies, or living situations. For example, references to new family roles or interests may appear.
4. **Social and Political Identity:** Users may update their bios to reflect current social or political issues, aligning their identity with broader movements or causes they support.
5. **Branding and Presentation:** Over time, users may refine how they present themselves, adopting more polished or strategic language to reflect personal branding or audience engagement goals.
6. **Technological and Cultural Trends:** The evolution of language, references to cultural phenomena, or the use of emojis and hashtags can reflect broader technological and cultural trends.
7. **Disappearance of Information:** Some users may choose to simplify or remove information, which could indicate a desire for privacy, a shift away from self-promotion, or a change in how they wish to be perceived online.

By analyzing these changes, we can gain insights into how individuals' presentations of self evolve in response to personal growth, external influences, and broader societal trends.

Revised Question: Tell me more about 4 Social and Political Identity. Provide two examples. Use quantitative analysis to show me what you learned.

OPTS Mark 1: To delve deeper into the aspect of "Social and Political Identity" in Twitter bios, I'll analyze changes that might reflect users' engagement or identification with social or political movements, causes, or affiliations. For this, I'll look for specific keywords or phrases that indicate a shift toward or emphasis on social or political identities between 2015 and 2020.

I'll conduct a quantitative analysis to identify two examples where users have updated their bios in ways that suggest a change in their social or political identity. To do this, I'll:

1. Identify common social or political keywords or phrases that emerged or became more prevalent in 2020 compared to 2015.
2. Quantify the occurrences or changes in these keywords or phrases between the two time points.
3. Select two examples that illustrate significant changes in social or political identity expression.

Let's begin this analysis.

*[Author's Note: OPTS Mark 1 composed and executed code to compare word counts from the Early\_Bio and Later\_Bio columns. It filtered the list to only include words that increased in count. Then it ranked the list from most-increased words to least.]*

The quantitative analysis reveals two keywords that increased in frequency in users' Twitter bios, suggesting a heightened emphasis on social and political identity between 2015 and 2020:

**Activist:** The term "activist" showed an increase, which suggests that more users began identifying as activists or associating themselves with activism. This could indicate a rise in political engagement or a greater willingness to publicly align with causes or movements.

**Equality:** The term "equality" also became more prevalent, pointing to a growing concern or focus on issues related to equality, such as gender equality, racial equality, or LGBTQ+ rights. This shift might reflect broader societal trends or increased awareness and advocacy around these issues.

*[Author's Note: It is not clear how or why OPTS Mark 1 chose Activist and Equality. In the comments of its code, OPTS Mark 1 called these two words "Mock example keywords," and inserted a long comment that included the sentence: "Assuming we have a predefined list of social/political keywords (e.g., based on prevalent issues in 2020), we would filter increased\_words using this list."]*

To illustrate these changes with examples, I will identify two users whose bios in 2020 included these terms, showing an evolution from their earlier bios that lacked these keywords. This comparison will highlight how their self-expression shifted to include these social or political identifiers.

Here are two examples illustrating the evolution of users' Twitter bios to include social and political identity elements:

*[Author's Note: I removed the rest of the response. The response gave the full text of two users' early and late bios.]*

### Signifier-Level Change

**Initial Question:** I call the words, emojis and other linguistic tokens used within bios "signifiers." Which signifiers were most likely to be added from 2015 to 2020? Which signifiers were most likely to be removed?

**OPTS Mark 1:** To identify the signifiers most likely to be added or removed from the Twitter bios between 2015 and 2020, I will analyze the provided CSV file. I'll compare the frequency of words and emojis in the bios from both years to determine which ones have increased or decreased in prevalence. Let's begin by examining the data to identify these trends.

The dataset shows a user's bio in 2015 ("Early\_Bio") and the same user's bio in 2020 ("Later\_Bio"). I will now analyze the changes in signifiers (words, emojis, etc.) between these two years. I'll calculate which signifiers were most frequently added and removed during this period. Let's proceed with the analysis.

The analysis reveals the following trends in signifiers between 2015 and 2020 in the Twitter bios:

Most likely added signifiers:

1. '@' - Possibly indicating an increase in mentions or connections to other users.
2. '/' - May signify more links or a separation of phrases and concepts.
3. '|' - Another form of separating different pieces of information.
4. '#' - Reflecting an increase in hashtag usage.

5. ' - A punctuation mark that became more common, likely in contractions or possessives.
6. " - This character often accompanies emojis.
7. '\u200d' - A zero-width joiner, typically used in complex emojis or special characters.
8. '•' - Bullet points, possibly used for list formatting.
9. 'she' - Increased usage, potentially indicating more gender identification or discussions.
10. 'her' - Similar to 'she', indicating more references to female subjects or ownership.

Most likely removed signifiers:

1. '.' - Reduced usage of periods could indicate less formal or shortened expressions.
2. "'" - Decrease in apostrophe usage, possibly fewer contractions or possessives.
3. 'i' - Lowercase 'i' becoming less common might suggest less personal narration or first-person expression.
4. 'and' - This conjunction's reduction might indicate less complex sentence structures or lists.
5. ',' - Reduced comma usage could suggest shorter, less complex lists or descriptions.
6. '!' - Exclamation marks becoming less common might indicate a shift in expressing excitement or emphasis.
7. 'the' - The definite article's reduction, possibly less formal or detailed descriptions.
8. 'a' - The indefinite article's decrease, similar trend as 'the'.
9. 'is' - Reduced usage of 'is' might indicate less static descriptions or present tense narration.
10. 'you' - Less direct address or second-person narration.

These changes could reflect broader trends in communication styles, the emphasis on connectivity and networking, or shifts in cultural and personal identity expression on Twitter.

Revised Question: Were 'he' and 'him' likely to be added? Answer by quantitatively comparing the change in usage of these signifiers to the rest of the distribution.

OPTS Mark 1: It seems there was a reference to an undefined variable `total_changes`. I'll correct that and focus on providing the change in usage for 'he' and 'him', as well as their ranks within the overall distribution of changes. Let's recalculate these values properly.

The changes in the usage of 'he' and 'him' between 2015 and 2020 are as follows:

- 'he': Increased by 1308 occurrences, ranking 17th among all changes.
- 'him': Increased by 1239 occurrences, ranking 19th among all changes.

Given the total number of unique signifiers analyzed (175,715), the changes in 'he' and 'him' are substantial, placing them within the top tier of added signifiers. This indicates that both 'he' and 'him' were indeed likely to be added during this period, significantly more so than the average for all signifiers.

*[Author's Note: Interestingly, OPTS Mark 1 – over the course of two prompts – brushed up against the trend of adding pronoun lists to Twitter bios – a phenomenon that is the subject of at least five academic manuscripts (Aponte Molina, 2023; Choi et al., 2023; Dorn et al., 2023; King & Crowley, 2023; Tucker & Jones, 2023).]*

### **Test Run: Predicting some Selves**

After I created and interrogated OPTS Mark 1, I decided to test it on its intended task. I composed the following four hypothetical 2015 bios, and gave the oracle one chance each to predict the 2020 bio.

### Conservative father of two

Initial Question: Use your data to learn how bios change. Get ready to predict bios. Here is a 2015 bio: "Conservative father of two." Predict the 2020 bio for this individual. Remember that Twitter bios are 160 characters maximum. Explain all changes.

OPTS Mark 1: Now, let's craft a plausible 2020 bio based on these observations:

"Conservative father of two, dedicated to family values and community engagement. Proudly advocating for educational reform and fiscal responsibility."

Explanation of Changes:

- **Maintained Core Identity:** The bio still centers on being a conservative father, maintaining consistency in personal identity.
- **Added Detail on Values and Engagement:** Reflecting potential personal growth or deeper involvement in community or political issues.
- **Introduction of Specific Interests:** Mentioning educational reform and fiscal responsibility suggests a refinement in the individual's political interests or advocacy areas, which is a natural progression for someone identifying as conservative.

*[Author's Note: I removed a lengthy preamble during which the oracle restated its purpose and plans.]*

### Progressive father of two

Initial Question: In a new session, I repeated the above prompt changing **only the source bio**. The new bio was "Progressive father of two."

OPTS Mark 1: Now, let's predict the 2020 bio:

2020 Prediction: "Advocate for change, dedicated dad of teens, promoting equality and sustainability. Engaged in local community and personal growth."

Explanation of Changes:

- "Advocate for change" keeps the progressive aspect but makes it action-oriented, reflecting a potential deepening of engagement.
- "Dedicated dad of teens" updates the father aspect to reflect the children's aging.
- "Promoting equality and sustainability" adds specific progressive causes, which might have gained more focus over five years.
- Inclusion of "engaged in local community and personal growth" suggests a broadening of interests and involvement, typical of personal development over time.

*[Author's Note: I removed a similar (but not the same) preamble during which the oracle restated its purpose and named ways in which bios might change.]*

### Conservative mother of two

Initial Question: In a new session, I repeated the above prompt changing **only the source bio**. The new bio was "Conservative mother of two."

OPTS Mark 1: Predicted 2020 Bio: "Conservative mother of two. Passionate about family values and education. Engaged in community service. Advocating for responsible governance. Proud American."

Explanation of Changes:

- Core Identity Retained: The essence ("Conservative mother of two") is kept, indicating ongoing priority on these aspects.
- Expanded Interests: Added interests and activities (community service, education advocacy) show growth and broader engagement.
- Updated Social Engagement: The mention of "responsible governance" and "Proud American" could reflect an increased interest in national issues, possibly influenced by events in the intervening years.
- Personal and Professional Growth: The bio reflects hypothetical personal growth and an expanded scope of identity and interests.

*[Author's Note: I removed a similar (but not the same) preamble.]*

#### Progressive mother of two

Initial Question: In a new session, I repeated the above prompt changing **only the source bio**. The new bio was "Progressive mother of two."

OPTS Mark 1: Here's a predictive attempt:

"Progressive mother of two, community activist, and advocate for education reform. Passionate about social justice and empowering the next generation."

Explanation of Changes:

- Role Expansion: Addition of roles like "community activist" and "advocate for education reform" indicates increased engagement or new responsibilities taken up since 2015.
- Consistency in Core Values: The term "Progressive" is retained, ensuring continuity in self-identity.
- Interest Specification: Adding specifics like "social justice" and "empowering the next generation" provides depth to the bio, indicating areas where the user may have focused their efforts or advocacy.

This prediction maintains the essence of the individual's 2015 identity while accounting for potential growth and engagement in related areas.

*[Author's Note: I removed a similar (but not the same) preamble.]*

## Discussion

Overall, I was disappointed but intrigued. *OPTS Mark 1* appeared to understand what I asked of it and the data I provided. But the casual, natural language queries above yielded wordy replies that were not entirely vacuous, but filled with equivocal language. (May and might were frequently used.) Nevertheless, I predict that – with a refined process and more iteration – these same tools will lead to a better oracle.

As much as it is scoffed at, there is something to the idea of "prompt engineering." Millions of dollars have been spent for LLM chatbots to learn; the operators of those chatbots also need to spend time learning and practicing the art of extracting value from them. It has been my experience (in a fiction-writing context) that custom GPTs **are** capable of combining GPT-4's world knowledge, user-provided data and custom instructions to produce consistent and creative narratives. Considerable user patience

and persistence was required, however. I will attempt to further refine OPTS to break it of its habit of lazy, surface-level responses.

Consider the four predictions I asked of *OPTS Mark 1*. They are not "wrong," but neither are they insightful. With some prodding, I imagine an *OPTS* system would provide more detailed, specific predictions. To explore this, I gave *OPTS Mark 1* the following prompt: *Consider the 2015 bio: "Conservative father of two." Is this user more likely to have added "MAGA" or "BLM" to their 2020 bio?* Here was the response:

Based on the data analysis, among users who described themselves as "Conservative" in their 2015 bio, 53 of them added "MAGA" to their 2020 bio, while none added "BLM." Therefore, it is more likely that a user with the 2015 bio "Conservative father of two" would have added "MAGA" rather than "BLM" to their 2020 bio.

When I altered the prompt to replace "conservative" with "progressive," *OPTS Mark 1* used the same analysis to conclude BLM was more likely. It did the same for "liberal." The knowledge and capability are locked away, and persistence is a key.

### **Immediate Next Steps**

The oracle needs better instructions, and the operator needs more experience. *OPTS Mark 1* seems to know exactly what I asked of it, but there is a disconnect between what it delivers and what I desire. *OPTS Mark 1*'s conclusion that bios mark both "stability and change" is true, but abstract to the point of fortune-cookie inanity. I hoped for more specificity. After I prompted the system to look for known trends, it surfaced evidence for them. But I will need to work further on prompt structure if I expect *OPTS* to provide automated discovery.

### **Longer Term Goals**

It would be easy to expand the breadth of data available to the oracle. First, I could add annual longitudinal and cross-sectional data. Ideally, this would provide the opportunity to dissociate aging and historical effects. With the current architecture, there is no way for the system to know what revisions are due to five years passing versus what revisions were simply popular in 2020. I could also add multinational data (e.g. Handzlik et al., 2024) to test the oracle's ability to generalize across nations and languages.

In the future, I will make a version of *OPTS* widely available, but two things caused me to hesitate to do so at this time. First, a ChatGPT Plus subscription is required to chat with custom GPTs, unfortunately. Second, when the custom GPT creator allows it to use code and knowledge files, it is easy for any interlocutor to convince the custom GPT to divulge the contents of the knowledge files. As I have done elsewhere, I prefer to not make raw biography texts available, but rather analysis at the level of aggregations.

### **Conclusion**

Ultimately, my goal is to develop *OPTS* into a *general identity forecasting system*. This system must be proficient at predicting how individuals will describe themselves in the future. Ideally, it would also provide explanations justifying its predictions.

A hard problem that I have not addressed here is scoring these predictions. What makes one prediction better than another? One could imagine converting bios to word vectors and measuring the distance between prediction and observation in a latent semantic space. On the other hand, signifier

choice is important, and perhaps we should demand perfect word-to-word matching. In the worst case, we may "know it when we see it," and need human annotators.

Regardless, I believe it will be fruitful to construct **many** general identity forecasting systems and contrast their performance. These systems could be made of human experts in identity theory. They might be sequence-to-sequence machine learning systems as I originally envisioned. Or maybe we will welcome a new LLM-based oracle to predict the self as our new identity forecasting overlord.

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