# Leveraging LLMs for Automated Dream Coding

## Introducing DreamCoder

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LLM = Large Language Model

# My Journey into Dream Research

I've been logging my dreams regularly since 2023

- 341 total (June 20), Average ~5/wk
- I also keep a daily journal

My dreams often align with the Continuity Hypothesis

What drew me to quantitative dream analysis

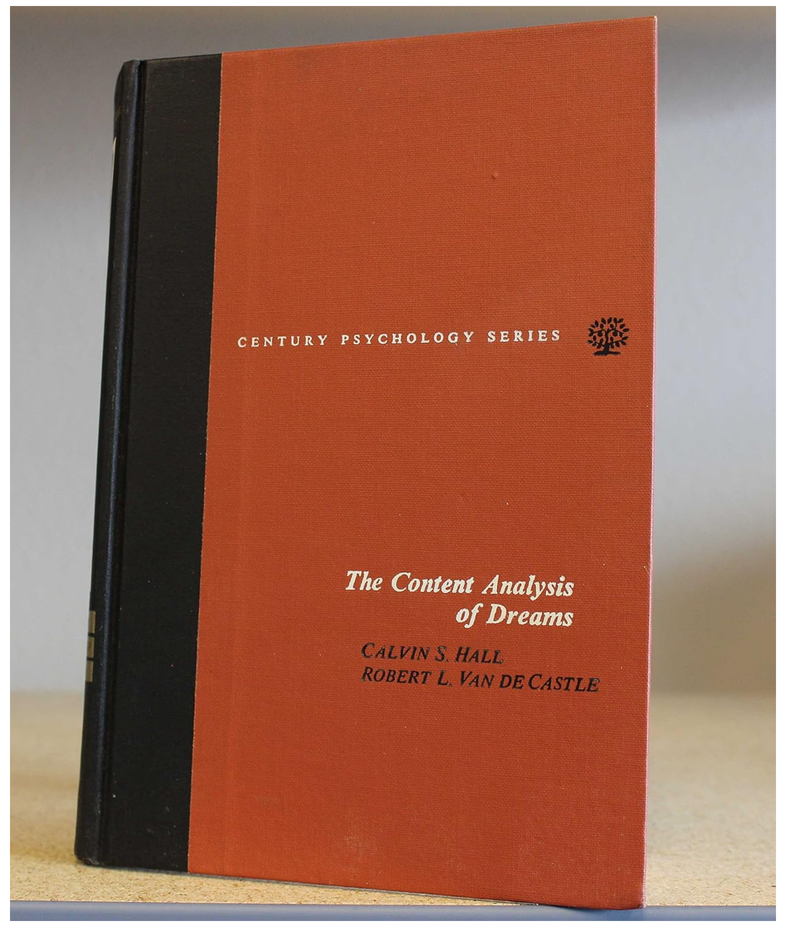
- **Lets the data speak.** Patterns naturally emerge from dream content
- **Reveals large-scale trends.** Analysis across individuals, cultures, time
- **Aligns with engineering mindset.** Focus on testable hypotheses and data-backed conclusions

Serendipity with AI skills**.** Large Language Models (LLMs) for dream content analysis

# Hall-Van de Castle (HVdC) Coding System

## 📘 Overview

- Developed in the 1960s by Calvin Hall and **Robert Van de Castle**
- Most widely adopted system for quantifying dream content
- Clearly defined coding rules → maximizes inter-coder reliability




*The Content Analysis of Dreams*
Hall & Van de Castle (1963)

the HVdC coding "bible"

## 10 Content Categories → dream elements to be quantified

- **Characters** – person (+ attributes), animal, creature
- **Social Interactions** – aggression, friendliness, sexuality
- **Emotions** – anger, apprehension, sadness, confusion, happiness
- others – Success & Failure, Settings, ..

## Content Indicators

- Quantitative measures of key aspects of dream content

  Examples: **Male %**, **Aggression %**
- Profile of dreamer's relationships, emotions & concerns

### ✅ Steps in HVdC Dream Analysis

1. Identify dream elements and assign HVdC codes
2. Count category frequencies & compute Indicators
3. Compare metrics to norms or other baselines

# Barriers to Adoption

Hard to become proficient

- Dozens of rules, many requiring nuanced interpretation

Manual coding is labor-intensive → makes large-scale analysis difficult

**What if ?**

Coding dreams is as simple as... pressing a button


# What are Large Language Models (LLMs)

Commonly used: ChatGPT, Gemini, Grammarly

A type of AI that generates human-like text:

✏️ **Summarizing** – "Summarize this dream"

🌐 **Translating** – "Translate to Spanish"

🧩 **Completing** – "Finish the story: I went to a party and met ..."

📅 **Planning** – "Create a 5-day itinerary"

LLMs excel in following instructions → ideal for structured analysis of dream content

Prior studies used Language Models, with limitations

- Bertolini et al. (2023) - Only codes for presence/absence of Emotions
- Cortal (2024) - First LLM-based dream coding; codes HVdC with simplifications (e.g., Family → 'Known')

LLMs have limitations:

1. Hallucination - generate false information
2. Attention limits - may "forget" some details of a long or complex input

# DreamCoder - software for Automated Dream Coding

## ⚙️ Key Features

- Generates full HVdC codes from dream content
  - Currently codes for: **Characters**, **Social Interactions**, **Emotions**
- Uses GPT-4.1 (OpenAI's advanced LLM) for accurate coding

## 🚀 The Promise

- **Effortless dream coding.** AI handles the heavy lifting; just review and refine
- **More time for insights.** Researchers focus on analysis, not manual coding
- **Affordable at scale.** \$0.01 to \$0.02 per dream → 1M dreams for \$20K

# How DreamCoder Works

1 Identify known characters from the narrative

2 Insert dream text & cast into the User Prompt.

3 Instruct LLM to find elements & infer attributes

4 Assign HVdC codes based on attributes.

Abigail invited her niece to the zoo.

Cast Finder

Cast of Characters

Abigail, F, Aunt, father's sister
Abner, M, Cousin, Aunt Esther's son
Agnes, F, Grandmother, paternal
...
Zach,M,Friend,

**User Prompt**

Abigail invited her niece to the zoo.

Abigail, female, aunt

**System Prompt**

Character rules

Social rules

Emotion rules

LLM
(GPT-4.1)

- One LLM call per Category

Annotations


```
"characters": {
  "elements": [
    {
      "index": 1,
      "text_fragment": "Abigail",
      "start": 1,
      "end": 8,
      "number": "individual",
      "entity_attributes": [
                 "person", "alive"],
      "gender": "female",
      "relationship": "aunt",
      "identity": "relative",
      "age": "adult"
    },
    {
      "index": 2,
      "text_fragment": "her neice",
      "start": 17,
      "end": 26,
      "number": "individual",
      "entity_attributes": [
                  "person", "alive"],
      "gender": "female",
      "relationship": "niece of aunt",
      "identity": "relative",
      "age": "juvenile"
    }
```

```
"social": {
  "elements": [
    {
      "index": 1,
      "text_fragment": "invited",
      "start": 9,
      "end": 16,
      "actor": "1",
      "receiver": "2",
      "level": "invitation",
      "modifiers": [],
      "interaction_type": "friendliness"
    }
  ]
```


"individual", "female", "relative", "adult"

1 F R A

Code Assigner

- LLM doesn't assign codes to reduce errors (hallucinations)
- Python logic handles code assignment

# Partial Match Scoring

**Motivation:** Exact scoring is binary: match vs. not match

- does not distinguish minor from major differences.

*minor:* **1MBA** (**I**ndiv, **M**ale, **B**rother, **A**dult) ≠ **1MBT** (**I**ndiv, **M**ale, **B**rother, **T**een)

*major:* **1MBA** (**I**ndiv, **M**ale, **B**rother, **A**dult) ≠ **1FSA** (**I**ndiv, **F**emale, **S**tranger, **A**dult)

both have Exact Score = 0

Partial scoring measures subtle coding differences

- Assigns greater weights to more important attributes

| Number 10% | Gender 40% | Identity 40% | Age 10% |
|---|---|---|---|
| **1** | **M** | **B** | **A** |
| **1** | **M** | **B** | **T** |
| 0.1 | 0.4 | 0.4 | 0.0 |

**Partial Score = 0.9**

| Number 10% | Gender 40% | Identity 40% | Age 10% |
|---|---|---|---|
| **1** | **M** | **B** | **A** |
| **1** | **F** | **S** | **A** |
| 0.1 | 0.0 | 0.0 | 0.1 |

**Partial Score = 0.2**

*"My brother is sad."*

**1FSA** **SD, 1FSA**

**0.2** **1.0**

**Mean = 0.6**

Dream Score = mean Partial Score of elements

# Coding Performance

- Example dream texts from Hall & Van de Castle's (1963) book were input into DreamCoder
- **Strong agreement**. *Mean Partial Score* = 0.84 across five Categories

| | Characters | Aggression | Friendliness | Sexuality | Emotions |
|---|---|---|---|---|---|
| **Partial Score** | 0.86 | 0.83 | 0.87 | 0.74 | 0.90 |
| **Exact Score** | 0.64 | 0.60 | 0.53 | 0.72 | 0.75 |
| Number of dreams | 28 | 20 | 31 | 9 | 8 |

# Agreement with Published Results

**Reference:** 250 dreams from Barb Sanders[1] dataset, manually coded and profiled by Dr. William Domhoff's research team [2]

**Results:** Overall results aligned well (75% within ±5%), with refinements identified

### Dream Set 1 (N=125)

| | Metric | Manual | DreamCoder | Difference |
|---|---|---|---|---|
| **Characters** | Male % | 58.4% | 58.3% | -0.1% |
| | Familiar % | 38.4% | 43.2% | 4.8% |
| | Friends % | 20.0% | 25.1% | 5.1% |
| | Family % | 14.9% | 15.1% | 0.1% |
| | Animal % | 7.2% | 6.9% | -0.3% |
| **Social Percents** | Aggression/ Friendliness | 48.7% | 45.1% | -3.6% |
| | Befriender % | 48.6% | 48.5% | -0.1% |
| | Aggressor % | 53.1% | 54.8% | 1.8% |
| | Physical Aggression % | 29.4% | 23.8% | -5.6% |
| **Dreams with at least one** | Aggression | 52.0% | 60.0% | 8.0% |
| | Friendliness | 52.8% | 67.2% | 14.4% |
| | Sexuality | 21.6% | 18.4% | -3.2% |

### Dream Set 2 (N=125)

| | Metric | Manual | DreamCoder | Difference |
|---|---|---|---|---|
| **Characters** | Male % | 48.6% | 49.3% | 0.7% |
| | Familiar % | 33.5% | 36.8% | 3.3% |
| | Friends % | 10.6% | 15.1% | 4.5% |
| | Family % | 19.0% | 18.9% | -0.1% |
| | Animal % | 6.0% | 7.1% | 1.1% |
| **Social Percents** | Aggression/ Friendliness | 49.1% | 42.3% | -6.8% |
| | Befriender % | 56.4% | 58.6% | 2.3% |
| | Aggressor % | 48.1% | 52.6% | 4.5% |
| | Physical Aggression % | 33.1% | 24.9% | -8.3% |
| **Dreams with at least one** | Aggression | 56.0% | 57.9% | 1.9% |
| | Friendliness | 53.6% | 59.5% | 5.9% |
| | Sexuality | 18.4% | 15.9% | -2.5% |

**Agreement Legend**

- Strong (< 2%)
- Fair (2-5%)
- Poor (> 5%)

The 250 dreams were coded in ~40 minutes for under $4 USD (for OpenAI LLM calls)

1 Barb Sanders is an pseudoname for a woman who contributed over 3,000 dreams from her dream journal to DreamBank.

2 Table 5.3 in Domhoff (2003), The Scientific Study of Dreams.

# Example: Coding dreams in different languages

| | |
|---|---|
| English | Abigail invited her niece to the zoo, making her giddy with anticipation. |
| | Abigail: 1FRA; invited: 1FRA 5> 1FRC; her niece: 1FRC; giddy with anticipation: HA, 1FRC |
| Spanish | Abigail invitó a su sobrina al zoológico, lo que la hizo saltar de la emoción. |
| | Abigail: 1FRA; invitó: 1FRA 5> 1FRC; su sobrina: 1FRC; saltar de la emoción: HA, 1FRC |
| German | Abigail lud ihre Nichte in den Zoo ein und der Zoobesuch ließ sie ganz aufgeregt werden.[1] |
| | Abigail: 1FRA; lud … in den Zoo ein: 1FRA 5> 1FRC; ihre Nichte: 1FRC; ganz aufgeregt: AP, 1FRC |
| Japanese | アビゲイルが姪を動物園に誘うと、彼女は大喜びで楽しみにしました。 |
| | アビゲイル: 1FK*A; 姪: 1FRC; 動物園に誘う: 1FKA 5> 1FRC; 大喜び: HA, 1FRC; 楽しみにしました: HA, 1FRC |

- Promising results across 4 different languages, based on limited data
- Can further improve with fine-tuning

* Not coded as (R)elative—name was in Japanese, Cast list is English-only

1 With thanks to Johan Matte for the German translation

# Key Contributions to Dream Research

| Innovation | Benefits |
|---|---|
| 1. General-purpose LLM for coding | • Prompts makes it easy to define coding behavior, even for non-experts<br>• Advanced LLMs enable dreams to be coded precisely to HVdC rules<br>• Supports multiple languages |
| 2. Social Character modeling<br>• use dreamer's social context (Cast of Characters) | • More precise coding for Characters in the dream<br>e.g. "cousin" = **R**elative vs. **K**nown<br>• Relationship context improves Social Interaction analysis<br>"*My **friend** grabbed my hand*" vs. "*A **stranger** grabbed by hand*" |
| 3. Partial Match scoring | • Enables fine-grained, objective scoring<br>• Simplifies finding accuracy issues |

1,2 Also known as zero-shot and few-shot learning, respectively.

# What's Next

Software enhancements

- Improve accuracy of Aggression and Friendliness
- Send de-identified data when calling GPT (code dreams anonymously)

I'm eager to explore the unique insights HVdC coding can reveal

- Begin with analyzing my own dream data
- Collaborate with fellow dream researchers and practitioners

# Final Thoughts

Automated dream coding is no longer a dream—it's becoming a reality

- Less time coding, more time on meaningful insights

We're entering a new era of "big data" for dream research

- Easily code 1000s of dreams
- Enables large-scale comparisons across demographics, cultures, and time

Opportunity to blend quantitive dream content analysis with interpretive methods

Tools like DreamCoder can transform how we study the dreaming mind.

# References

**Bertolini, L., Fajcik, M., Sabo, O., & Smrž, P. (2023).** *Automatic scoring of dream reports' emotional content with large language models*. arXiv. https://arxiv.org/abs/2302.14828

**Cortal, G. (2024).** *Sequence-to-sequence language models for character and emotion detection in dream narratives*. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics and Language Resources (LREC-COLING)* (pp. 1449–1458). *https://aclanthology.org/2024.lrec-main.1282*

**Domhoff, G. W. (2003).** *The scientific study of dreams: Neural networks, cognitive development, and content analysis*. American Psychological Association.

**Hall, C., & Van de Castle, R. (1966).** *The content analysis of dreams*. Appleton-Century-Crofts.

**Riedl, M. (2023).** *A very gentle introduction to large language models without the hype*. Medium. https://mark-riedl.medium.com/a-very-gentle-introduction-to-large-language-models-without-the-hype-5f67941fa59e

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# Thank you!