

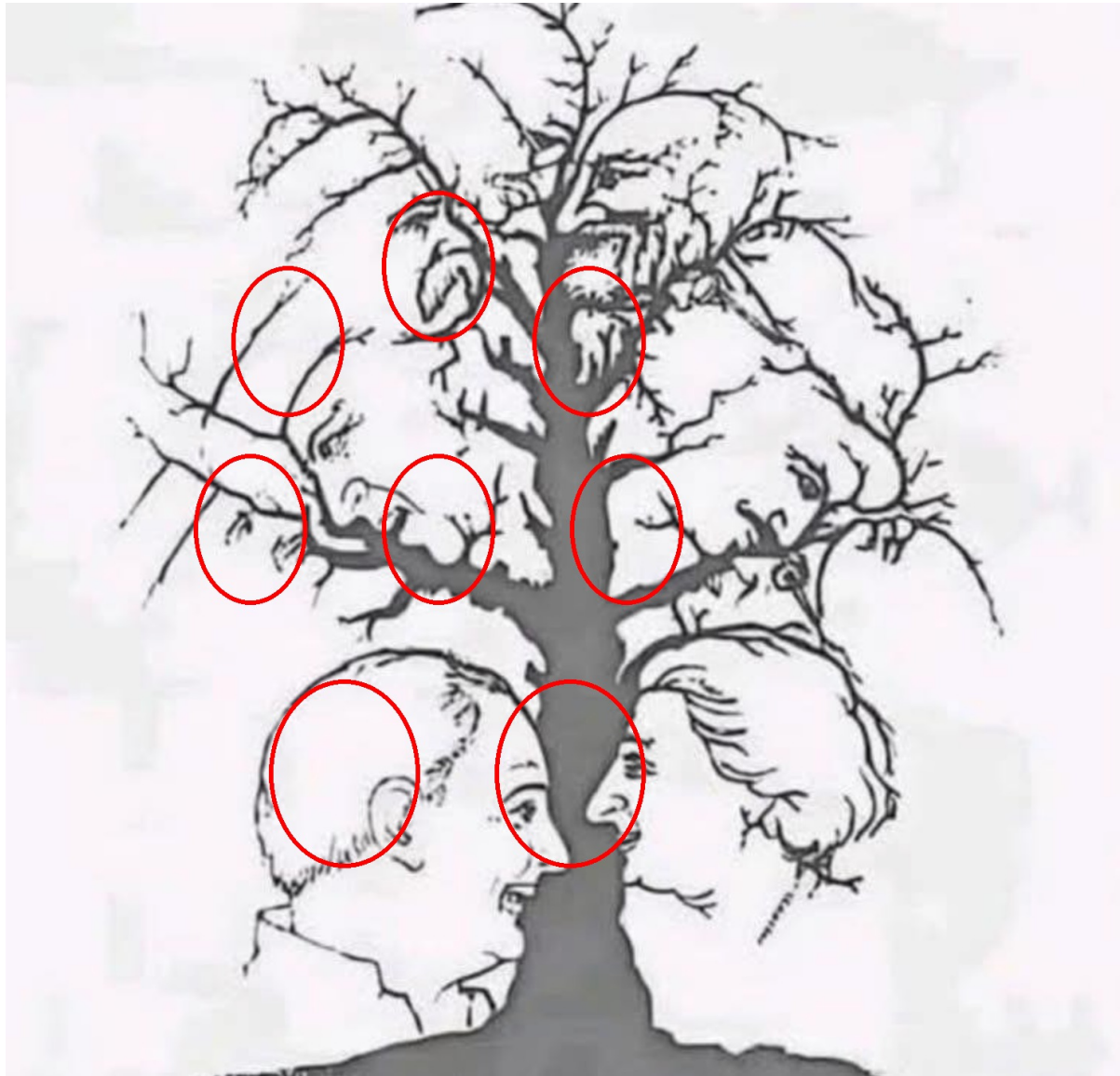
## ***Question asked***

how many faces do you see . mark the faces with red circle..

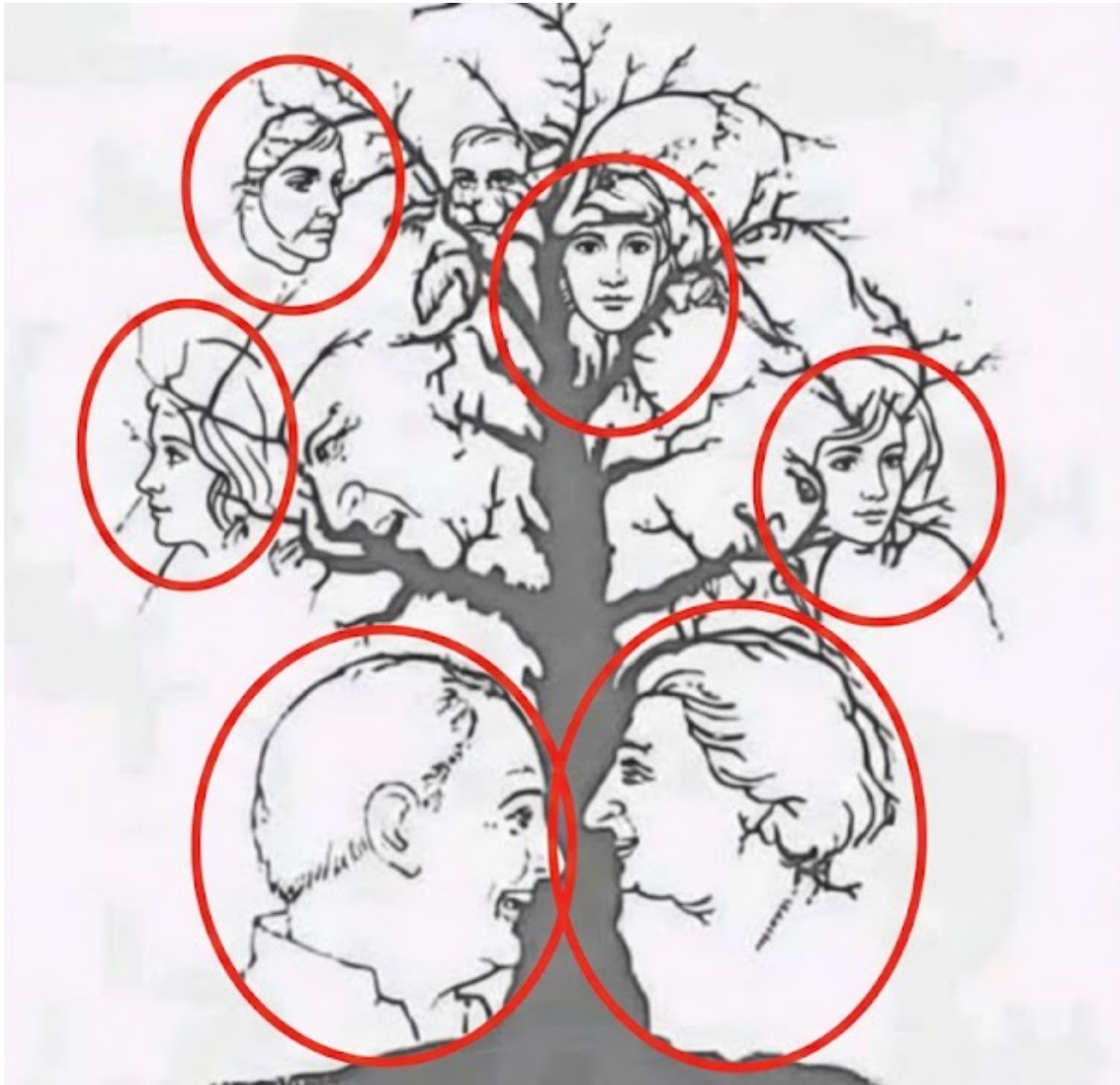
**Problem credit:**

*Yu-Ping Wang*

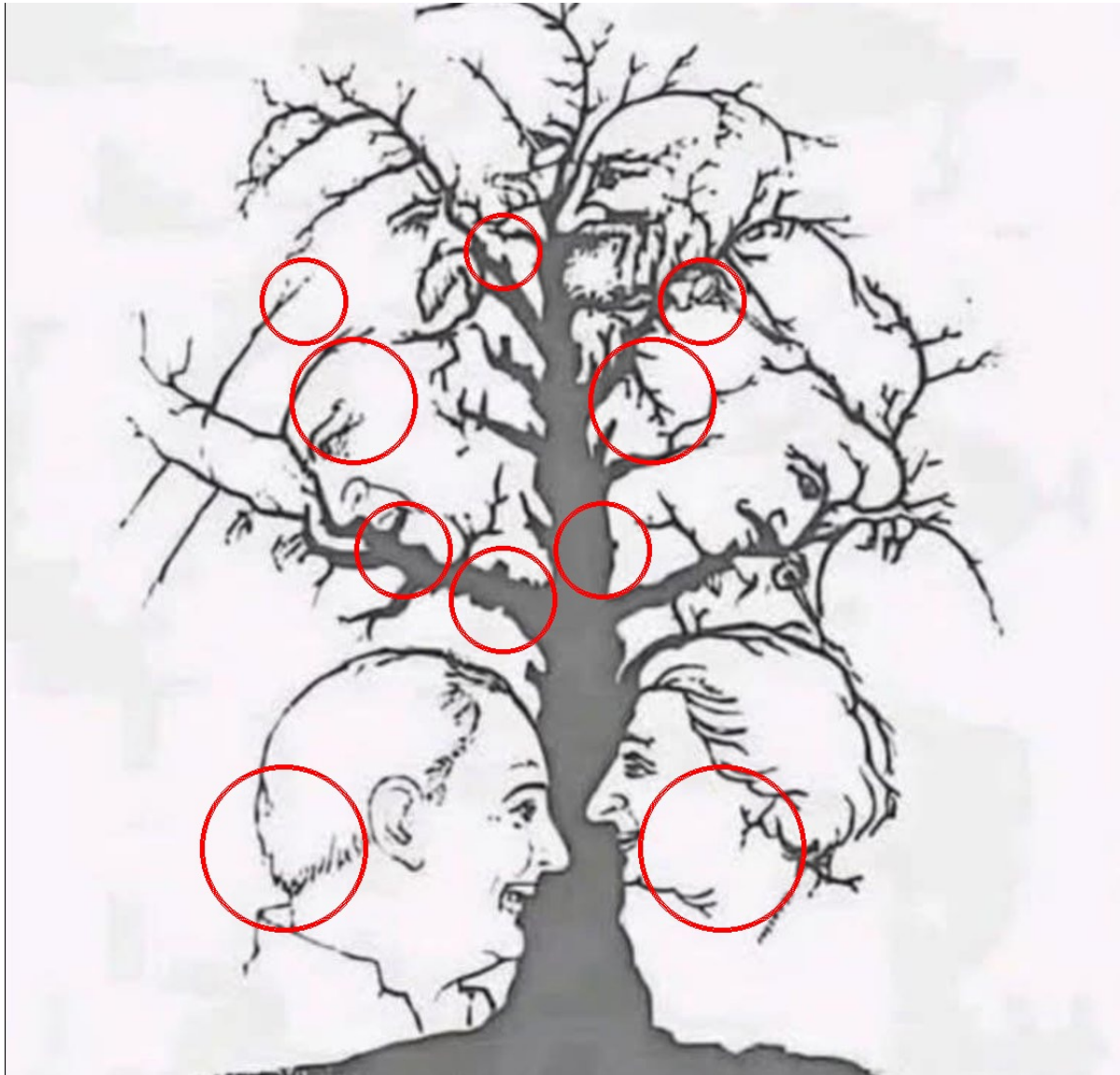
*Tulane University*



Chat-GPT  
**F-grade**



Chat-GPT  
**D-grade**



Claude  
**F-grade**

## Lack of **iterative hypothesis testing**

Iterative hypothesis testing is a general problem-solving process in which a system repeatedly proposes a possible explanation for observed data, evaluates how well that explanation fits, and then revises it until a satisfactory match is reached.

# Hypothesis Testing in Humans: Cognitive Process

Step 1: Form an initial hypothesis: “That shape is a dog.”

Step 2: Generate predictions: “If it’s a dog, I should see a tail and four legs.”

**Feedback loop**

Step 3: Compare prediction with sensory input:  
The brain checks whether the actual input matches expectations

Step 4: Compute error: If there is mismatch, brain registers prediction error.

Step 5: Update hypothesis: “Maybe it’s a fox instead.”



# Project 13: Iterative Hypothesis Testing with Topological Feedback

**Goal:** To design and implement an iterative hypothesis testing framework in which graph (or complex) structure is repeatedly updated using a feedback loop driven by topological constraints. In particular, students will use the Betti-1 number (the number of independent cycles in a 1-skeleton) as a global feedback signal to guide structural inference. The project demonstrates how topology can function as a principled constraint in adaptive model refinement.

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**Description:** A graph (or simplicial complex) will be treated as a hypothesis about the underlying structure of data. Students begin with noisy pairwise observations, such as simulated relationships or edge weights, and construct an initial graph that represents their first hypothesis. The graph is interpreted as a 1-skeleton, meaning that only vertices and edges are considered. The Betti-1 number is then computed to measure how many independent cycles exist in the current graph.

Students define a target structural property, such as a desired number of cycles. The algorithm then proceeds iteratively. At each step, the current graph is evaluated in two ways: how well it explains the observed data and how well its number of cycles matches the desired target. Based on this evaluation, edges are added or removed to improve the overall consistency. Each modification is not judged only by how it improves local data fit, but also by how it changes the global cycle structure of the graph. **The number of cycles therefore acts as a feedback signal that influences the next hypothesis.**

This iterative process continues until the graph both fits the data reasonably well and stabilizes in its topological structure. Students compare this topology-aware method to a simpler baseline method that ignores cycle structure. Through this comparison, they observe how topological feedback prevents the formation of spurious small loops, preserves meaningful global structure, and improves robustness under noise.

**Learning Outcome:** Students will understand *iterative hypothesis testing as a feedback-driven process* in which models are repeatedly refined in response to global structural constraints. They will gain insight into how the **Betti-1** number measures cyclic structure in a graph and how this topological quantity can actively guide inference rather than simply summarize it. Students will develop an appreciation for the difference between local structural optimization and global topological consistency, and they will learn how algebraic topology can be integrated into adaptive model refinement.