Category Learning

Theory & Experiment

Before we talk about categories

Operationalization

- We have a concept/construct we want to measure, but how?
  - What is complexity?
  - What is social class?
  - What is justice?
- Need objectivity!
- Agree on an operational definition
  - How we will measure the concept in our study, so we can talk about something concrete
  - Typicality as a rating on a 7-point scale

Categorization

- Previous discussion
  - Categorization is important
  - We naturally group things into categories
    - All the time, just about everything
  - Categories help us make sense of the world
- Not part of this discussion, but related
  - Social categorization (in-group/out-group)
  - Stereotyping (applying category attributes to an individual)

Category Members

- Not all members of a category are equally ‘good’
  - Good examples (typical)
  - Bad examples (atypical)
- We’re better/faster at recognizing typical examples (typicality effect)
  - That’s what you wrote up a few weeks ago
- This is consistent with prototype and exemplar models

But how do we learn categories?

Examples!

Induction

- The process of deriving general principles from particular facts or instances.
- We derive category attributes from shared attributes
- Note that some examples will be better/ more typical than others

Definition from the American Heritage dictionary

Category learning

David Hume (18th century Scottish philosopher)

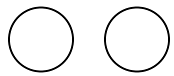
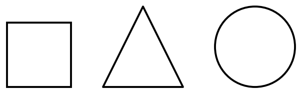
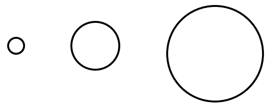
- The problem of **induction**: how do we generalize from a finite list of facts of examples to a general rule?
- What kind of properties do we notice?
- What kind of properties are there?
- How do we decide which properties of the examples are likely to be important in category and which are just details of the particular examples?
  - There is no strictly logical basis for forming firm generalizations from a finite number of observations.
  - That is why we should make educated guesses about what the general properties of the observed instances may be.

Categories, categories

- Not all are equal
- Some are easier to learn than others
  - Few essential attributes
    - ‘Red things’
      - Have to pick up on redness
    - ‘Balls’
      - Have to realize that they’re all round

Features

- First, we have to figure out what features are important.

- Types of features:
  - Binary or Boolean features (e.g., red vs. not red) 
  - Discrete features (e.g., square, triangle, circle) 
  - Continuous features (e.g., size, brightness) 

Features

- Relevant features:
  - If I tell you “This is an apple” and you’ve never seen one before, how will you know how to define “apple” as a category:
    - Size?
    - Shape?
    - Color?
    - Taste?
    - Function (something to eat)?
    - Texture?
    - Origin?

Induction is like educated guessing

- We can always assume that we are lacking some information that would change the definition.
  - Just one counterexample could disprove our set of rules.
  - **Every possible object** must be considered to truly prove that a definition is correct—but in the real world, we rarely have contact with all possible examples.

Category learning

- Categories differ in the ease people learn them from examples.
- Simple categories can be learned from a few examples (e.g., chairs), while complex categories can be extremely disjointed (e.g., a set including a hat, a piano, the sun, and the King of Sweden).
- The latter category is so <u>incoherent</u> and <u>irregular</u> that it seems impossible to communicate the <u>essence</u> of the category.
- Therefore, these kinds of categories are hard to learn from examples.

Category learning

- The only way to communicate the contents of complex categories is by listing their contents, since there are <u>no regularities</u> or <u>commonalities</u>.

- Therefore, a complex category is one that cannot be <u>compressed</u> or <u>summarized</u>.

Are complex categories harder for people to learn?

- Intuitively, it makes sense that complex categories should be harder to learn.
- But as scientists, we need a rigorous definition of complexity if we want to empirically demonstrate that complexity makes learning more difficult.
- If we say that a complex category is one that's hard to learn, our argument becomes circular.
  - What's a complex category? One that's hard to learn.
  - What kinds of categories are hard to learn? Complex ones.
- We need to *operationalize* complexity.

Boolean Complexity

- Some combinations of properties can be reduced
  - Big ball or small ball:
  - 1 attribute: ball (no need for size)
- Some cannot
  - Big ball or small box:
  - 4 attributes: cannot be collapsed
- Higher the number, the more complex

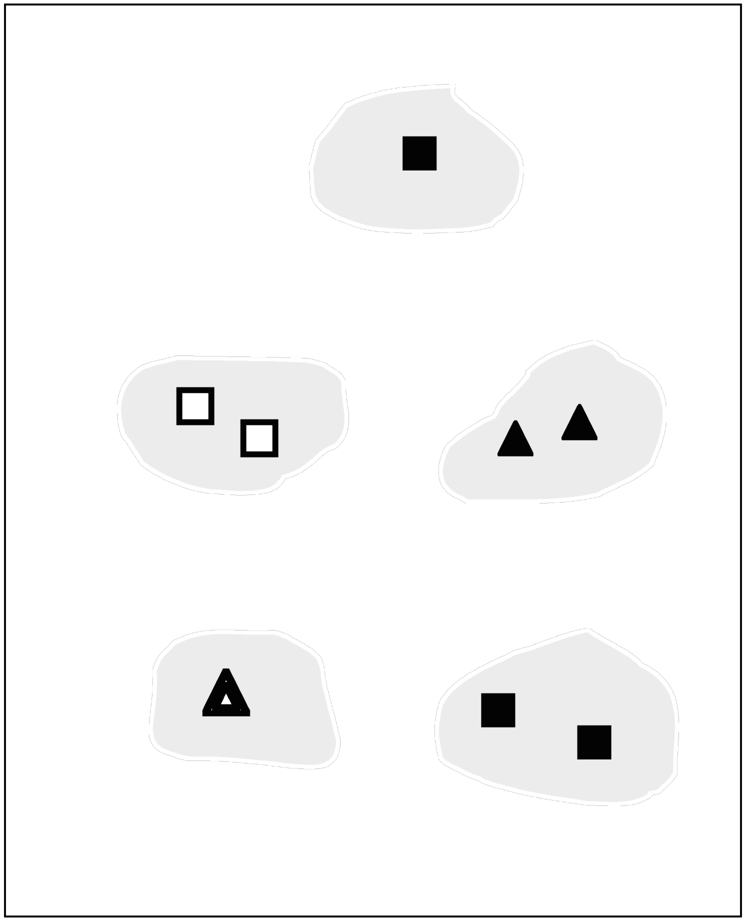
In today's experiment

- 3 binary attributes
  - 1 or 2 nuclei
  - Triangle or square nuclei
  - Filled or unfilled nuclei
- 8 possible amoebas
  - Your job will be to see & remember what amoebas are part of the category

Boolean complexity

Amoebas in:

- Category 1 have black square nuclei
  - Black & square ⇒ Complexity II
- Category 2 have two white squares or two black triangles nuclei
  - Two[White Square or Black Triangle] ⇒ Complexity V
- Category 3 have one white triangle or two black square nuclei
  - One White Triangle or Two Black Square ⇒ Complexity VI



Boolean complexity

	BOOLEAN COMPLEXITY
2 white triangles 2 white squares	**2**
1 white triangle 2 black squares	**6**
1 white triangle 1 black square	**5**
1 black square 2 black squares	**2**

Parity may also effect category learning

- Parity = the number of negative vs. positive examples of a category we see.
  - Positive example: this object is red.
    - NOTE: “positive” in this context does NOT mean “good”.
  - Negative example: this object is **not** red.

- People may have a *positive bias.*
  - There are a lot more “Not Red” things in the world than “Red” things.
  - Therefore, it is more informative to say that something is “Red” than “Not Red”.
  - So people may be inclined to put more emphasis on positive information than negative.

Today's Experiment

- Investigate the effect of complexity & parity on learning categories
  - See 8 amoebas
    - Nucleus number
    - Shape
    - Filled/unfilled
  - Learn the category from examples
  - Test to see if you learn it

Category learning and complexity

First I.V. = **Complexity**

- We will operationalize complexity to mean Boolean complexity (the number of descriptors that are necessary to define the category).
- Three levels: complexity II, V, and VI.

Category learning and parity

- Second I.V. = **Parity**

- Two conditions:
  - “Up parity” = 2 positive examples and 6 negative
  - “Down parity” = 6 positive examples and 2 negative

- Parity does not change as a function of complexity, so we can create both up parity and down parity trials for each level of complexity.

Category learning

- D.V. = **Difficulty in learning the category**
- We will operationalize this as the % of amoebas correctly categorized after the subject is given time to learn the category.

Theories and hypotheses

- Theory 1: Complexity makes learning more difficult.
  - Hypothesis 1: Subjects will make more mistakes categorizing more complex groups.

- Theory 2: People are more inclined to focus on positive examples of a category.
  - Hypothesis 2: Subjects will make more mistakes categorizing groups with down parity than up parity.

Analysis: 2x3 ANOVA

- Theory 1: Complexity makes learning more difficult.
  - Hypothesis 1: We expect a *main effect* of complexity on percent correct.
- Theory 2: People are more inclined to focus on positive examples of a category.
  - Hypothesis 2: We expect a *main effect* of parity on percent correct.
- Interaction effect?

Real-world implications

- Integrating info together by a rule makes learning simpler.
- This could help explain why its easier to learn new information in a field we’re already familiar with.
- Could suggest mnemonic strategies (and learning by analogy)—look for the simplest link between distinct items.

Study limitations & future directions

- Our subjects will have prior knowledge of our hypotheses—may bias results.

- *External* or *ecological validity*—how much do our findings generalize to real-world settings?

- What could possibly account for any *unexplained variance* in our data?

Today...

- We’ll run the category experiment today.
- Save the data as catLearn-#### (last four digits of your student ID #).
- Follow the steps on the handout for importing into SPSS and e-mail the SPSS file to me at phelan.coglab@gmail.com. (stop there)
- Tomorrow we’ll analyze the data and talk about writing up an abstract.
- Remember, there’s information on these labs on my website and the lab web site: http://ruccs.rutgers.edu/~jacob/Psych306/labman.html

Primer on the experiment

- You'll be trying to learn categories by example
  - Categories of 'amoebas'
- The amoebas will differ on 3 attributes
  - # nuclei
  - Shape of nuclei
  - Whether the nuclei are filled
- Screen will be split into 2 halves, top & bottom
- Top half will have cat. members
- Bottom will have non-members
- They'll be displayed for 10 seconds

Primer on the experiment

- After this learning phase, you'll be tested on which were members and nonmembers
- All 8 amoebas will be presented
  - y for members
  - n for nonmembers
- Then it's time to learn another category

Let’s start it

- Go to the psy306 folder/Tuesday12
  - Find the shortcut to amoebas
  - Ignore the error message
- Enter the last 4 of your SS# as subject #
- Session is 1
- If you have any questions about what to do, say so now!
- Click OK and start the experiment