Prior Knowledge and Interaction Design

A Review and Case Study

Megan Campos | HFID 700

Introduction

Memory is the mechanism through which past experiences and information are stored in the brain. Long-term memory is encoded and stored in the brain for future access, and its capacity is unquantifiable (Bahrick, 1984). Long-term knowledge is highly organized and interconnected, and constantly evolving. This review describes the components of long-term memory, how people activate knowledge in long term memory, and explores how prior knowledge affects users of Excel and Google Sheets.

Schema Theory and Mental Models

Schema theory posits that people store knowledge categorically in their brains, and that that knowledge is refined by new experiences (Sternberg & Sternberg, 2017). Individuals draw schemas from memories and must activate those memories to react to a stimulus. As one matures and has more experiences, schemas become more refined, allowing the individual to distinguish between similar stimuli. As a result, schemas are intrinsically incomplete (Rumelhart & Norman, 1976). When interacting with a stimulus, the individual completes the gaps in the knowledge of the schema by way of assumption formation, and alters that assumption with new experiences (Rousseau, 2001; Stein, 1992). Schema organization is beneficial because it reduces cognitive load by dispersing experiences into components and forging connections between those components (Paas, Renkl, & Sweller, 2003; Sweller, 1994). Schemas also diversify the retained meaning of each stimulus, allowing people to create associations between different schemata for future use (Rousseau, 2001).

Schemas are the building blocks of mental models, helping people to connect prior knowledge with current experiences to more appropriately react in a given situation. Mental models are internalized representations of how people believe systems should function, and shape how they interact with that system (Johnson-Laird, 1983; Zwaan & Radvansky, 1998). Mental models comprise schemas, placing them in broad categories. Mental models are experience-based, and individuals re-allocate schemas as they have new experiences (Sternberg & Sternberg, 2017). Consequently, mental models cannot encompass the entirety of every system; in fact, they may come from separate systems with which users interact (Vosniadou & Brewer, 1992). As they accumulate new experiences, people refine their libraries of mental models, and draw from that library when confronted with a system.

Existing mental models serve as reference points for interactions with new systems. When someone encounters a new system, the attributes of that system activate a set of schema, which in turn trigger the most similar mental model the person has, allowing them to react to that system. Once the new interaction has occurred, the individual may augment the existing mental model or create an entirely new model (Staggers & Norcio, 1992).

Frames and Scripts

Frames are structured assumptions about a new situation, event, or interaction built around prior experiences (Minsky, 1974). Frames are hierarchical, with the upper levels containing certain, fixed information, and the lower levels containing slots that are filled by default information for the situation. Slots change depending on the situations or requirements of a situation. Slots are typically connected to other frames, creating a network of interrelated frame systems (Minsky, 1974; Sharples, Hogg, Hutchinson, Torrance, & Young, 1996). As with mental models, new information can cause an individual to modify a frame that alters the perception of an interaction and recodify that frame for later use. Similarly, scripts are a type of procedural schema that allow people to assume that events will follow a predictable course (Schank & Abelson, 1975; Sharples et al., 1996).

Together, frames and scripts can inform a designer's understanding of how users perceive and interact with an interface. Frames and scripts are useful in identifying predictable patterns of interactions, including what causes frustration and misunderstanding. Consequently, designers can use these predictions to create interfaces that ease the user into, rather than alienate them from, a new experience (Minsky, 1974; Schank & Abelson, 1975; Sharples et al., 1996)

Semantic Network Models

The individual components of long-term memory storage are intrinsically interconnected. Semantic network theory posits a model where knowledge nodes are organized hierarchically and based on understanding of the meaning of each individual node. The model can be visualized as a tree, with a central "trunk" concept linking to "branch" nodes of conceptual knowledge, which are then linked to other concept "branch" nodes. Propositional network theory, similarly, posits that the nodes are simplified into symbolic or abstract representations of objects and concepts, thereby improving cognitive economy and allowing for greater storage capacity (Pylyshyn, 1973). In this way, the whole of the individual's conceptual knowledge and understanding is intrinsically linked (Alan M. Collins & Quillian, 1969; Sternberg & Sternberg, 2017).

The hierarchical structure of the semantic network's nodes assigns lower-level conceptual nodes the attributes of the higher-level conceptual nodes in order to reduce redundancy and lighten the cognitive load. When a node is activated, that activation triggers reactions among connected nodes that might shift the order of processing (Sternberg & Sternberg, 2017). This means that interface designers should attempt to assist the user in establishing connections between readily accessible nodes of knowledge. If a concept is new and likely unfamiliar, designers can give the user visual clues that activate prime nodes, informing the user about how to interact with the new system.

Expertise, Learning, and Training

In instances where procedural knowledge is essential, people retain that knowledge and encode it in long-term memory. Experts are highly specialized and operate in high-complexity interfaces. Similarly, people with training or learning are familiar with, or have trace memories of, how to use a particular interface (Kieras & Bovair, 1984; Sternberg & Sternberg, 2017). For people with prior procedural knowledge, schema categorization may be specialized (Tuomi, 1999). This means interfaces designed for experts should map to their mental models. However, this also means that those with rigid expectations for how an interface should work might struggle to process deviations from those expectations (Sternberg & Sternberg, 2017). This is one reason that experts can be difficult to retrain to new systems and that designers should aim to streamline the transition from the old to the new. A designer can do this by referencing the expert's mental model. Similarly, designers should incorporate key activation points to access the trace memories of procedural knowledge in the trained user.

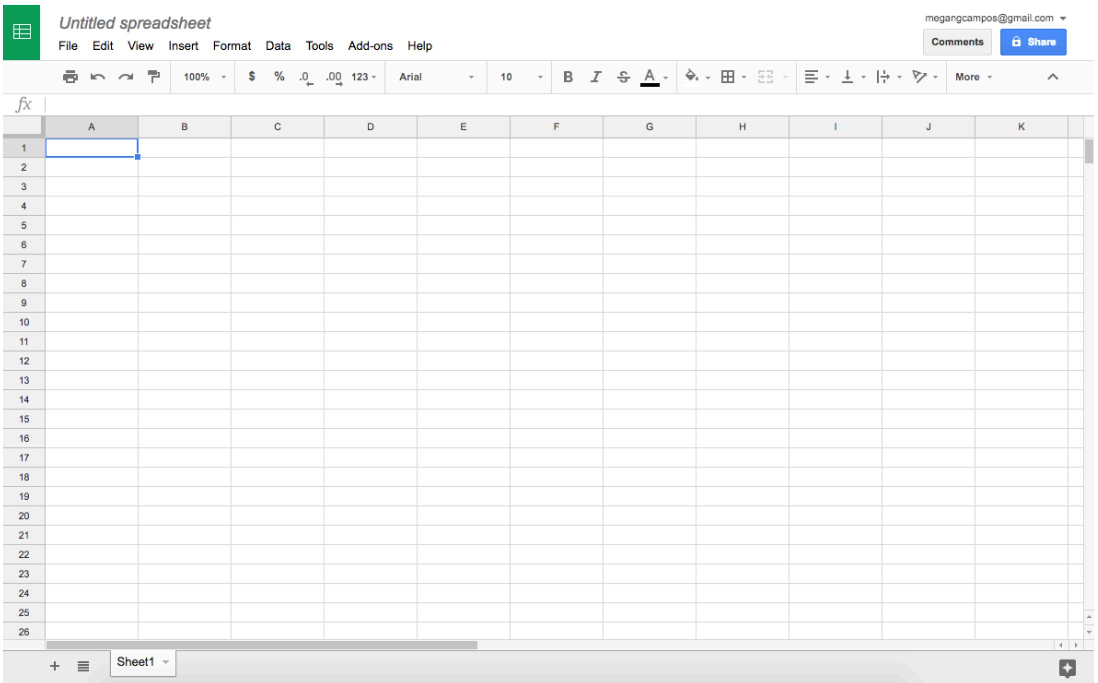
Spreading Activation and Fan Effect

Perceiving an object activates a prime node, which then activates a network of contextually related nodes. This is called the priming effect. The activated network spreads outward as relevant nodes are activated in a process called spreading activation. The pattern of spreading activation represents a concept, with a different pattern assigned to each concept available in that network (Allan M. Collins & Loftus, 2013; Sternberg & Sternberg, 2017). As people experience new systems, the process becomes more complex, and the spreading activation mechanism constantly evolves. As more nodes and connections are created, "fanning" out from the conceptual schema, the likelihood for error and the time to retrieve the necessary facts within a concept increases (Anderson & Reder, 1999). This concept is referred to as the fan effect. In the context of design, fan effect should be taken into account for its impact on the individual's ability to retain knowledge of how to use, interact with, or follow instructions for an interactive interface.

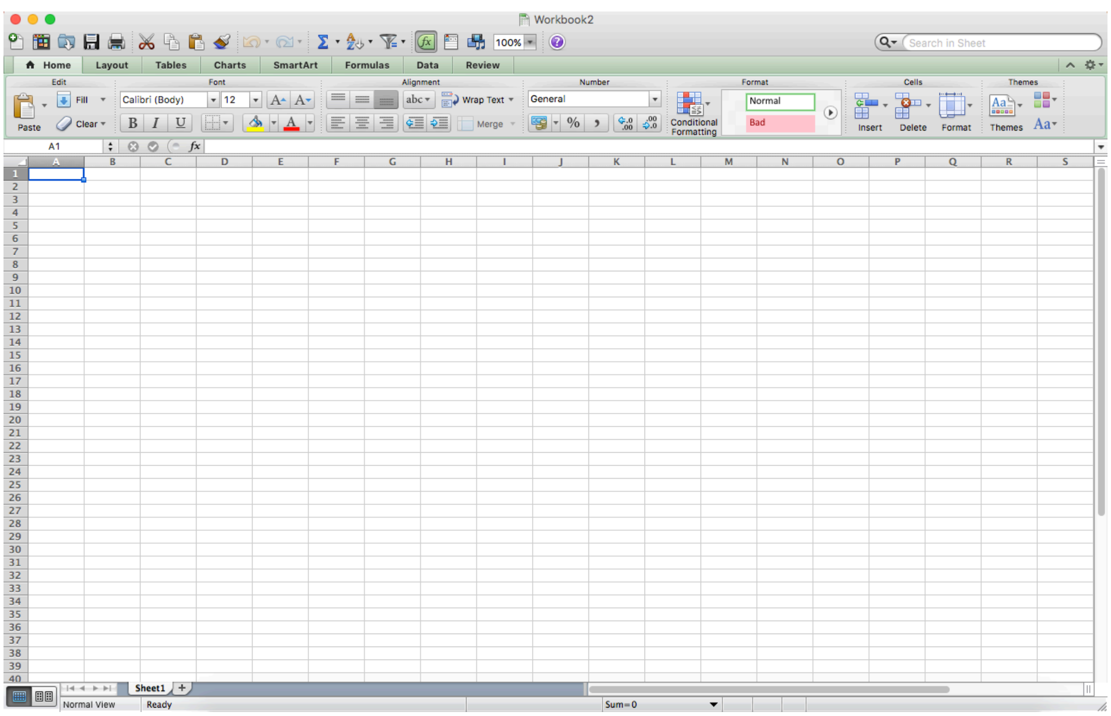
Frequency and Recency

Storing knowledge does not guarantee that schemas will not erode over time. The more one encounters a stimulus, the more the correlating network is activated, and the more quickly and successfully the appropriate schema is activated in the future. (Arbib, 1992; Standing, Conezio, & Haber, 1970). Similarly, the speed and accuracy of the recall schema increases or decreases depending on an encounter's recency. (Hintzman, 2001; Sternberg & Sternberg, 2017). When designing interfaces, designers should make the process of memory retrieval simpler for users by implementing easily recognizable elements and minimizing the depth of recall necessary to take the correct action. Additionally, designers should ensure that elements of sites that require user input or interaction are consistent in appearance, reaction, and function so that users can easily recognize each segment of the interface (Sternberg & Sternberg, 2017).

Case Study



Google Sheets

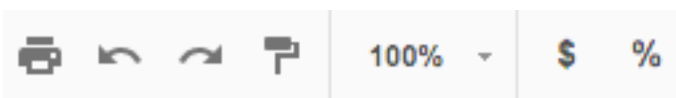


Microsoft Excel

Recently, Google launched its own suite of administrative tools to compete with Microsoft Office Suites. Google Sheets' design should attempt to marry the high-level conceptual node for data management systems (where the mental model is likely a system like Excel) with the high-level node for website applications (where the mental model is likely similar to other Google applications, such as Gmail), creating a semantic network for online data management systems. This network creates a set of understandings, expectations, and beliefs about how the online data management system should function and interact with the user. Should Google Sheets stray too far outside of those expectations, at least in the beginning, it could distress or frustrate user, potentially causing them to abandon the application altogether.

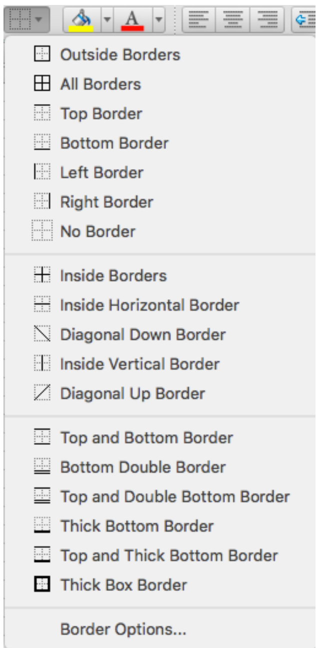
Sheets relies on a familiarity with the Excel interface to activate the conceptual nodes that will allow for intuitive navigation. For the novice user, who may have limited or no familiarity with Excel, Sheets does not offer significant introductory features. Excel uses several metaphors for basic functions, and the more experienced user would notice these in Sheets; Excel's printer graphic, for instance is abstracted into a flat, linear representative image.

Microsoft Excel Toolbar

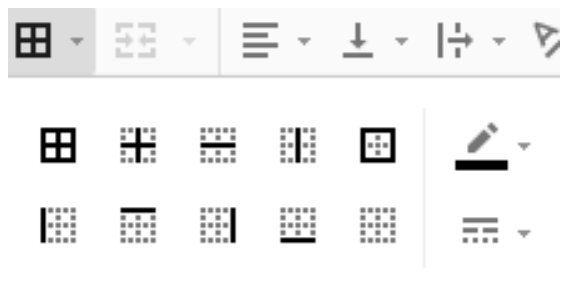


Google Sheets Toolbar

Users without complex mental models for these functions may not immediately comprehend the metaphor's form, which may cause confusion for the user. Similarly, in the areas where Excel's more abstract metaphors (such as the grid function) were duplicated nearly exactly in Sheets, the user might not have sufficient prior understanding to know what those icons mean without trial and error, which could serve to create additional confusion.

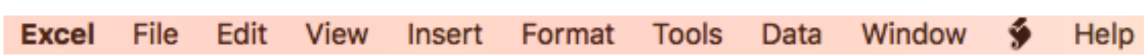


Microsoft Excel Borders

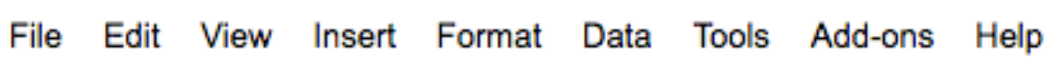


Google Sheets Borders

Sheets does succeed for the novice user in a few ways. Even if the user is not familiar with Excel, they are likely familiar with the idea of a toolbar. Sheets mirrors the Excel toolbar at the top of the page, giving the user a frame of reference that may inform the type of tool they are using. Elements in the toolbar—File, Edit, and View, for instance—may activate the schema for other desktop programs, as these are ubiquitous.



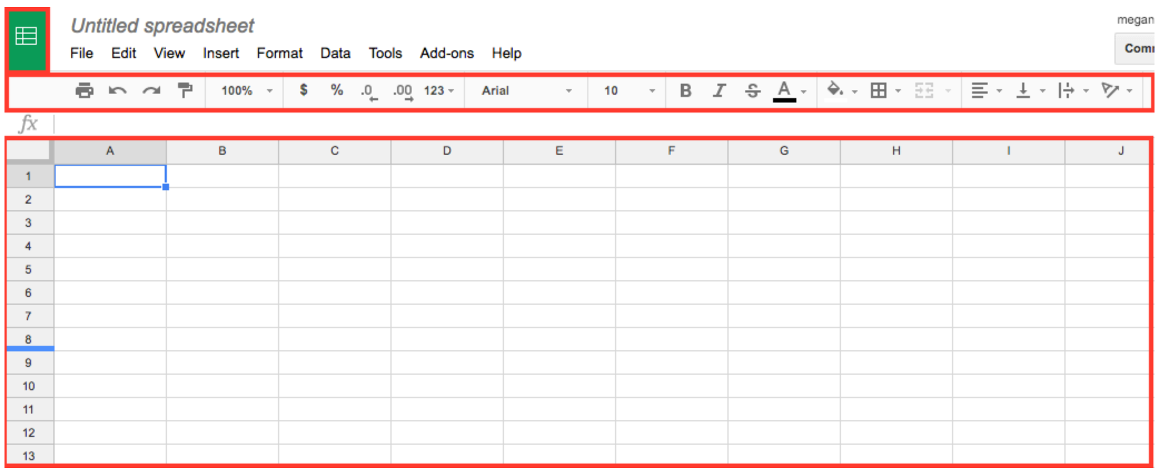
Microsoft Excel Toolbar



Google Sheets Toolbar

Depending on the prior knowledge from other programs, the novice Excel user may be able to use information gleaned from these familiar frames of reference to form a frame system, and further be able to inform their activation of the semantic network based on these attributes.

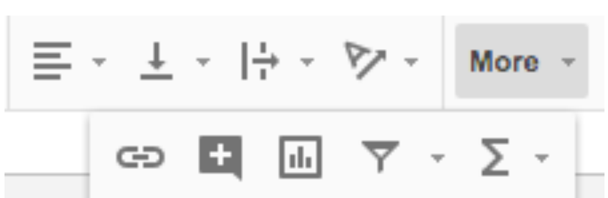
The occasional Excel user may be the most successful with Google Sheets. Occasional users of Excel have some training and learning, though perhaps do not use Excel's most complex algorithms. Occasional users are likely familiar with Excel's most basic functions, and thus will be able to activate the recall schema for that program based on the visual attributes in Sheets. At first glance, the use of green, the grid rows, and the minimized toolbar is reminiscent of Excel's interface, and may activate trace memories from past use.



Google Sheets, Excel-alike features indicated

Where novices might struggle with correctly mapping the metaphors to their usage due to the abstract nature of the icons, occasional users are likely to draw a strong connection from many of the icons that will further activate the appropriate nodes through spreading activation.

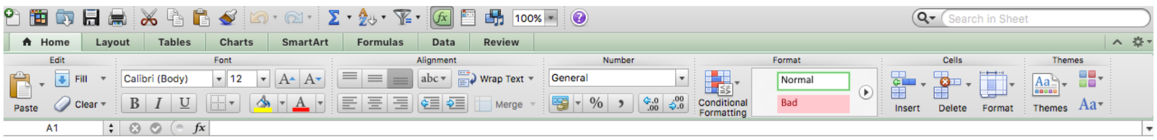
There is some schematic evolution required for the occasional user to correctly interact with Google Sheets. The toolbar is greatly minimized, so depending on their past interactions with Excel, the occasional user will lack some of the visual cues that may otherwise activate necessary nodes for total comprehension—the tools to create functions, for instance, are hidden behind a "More" dropdown rather than placed as an icon in the toolbar.



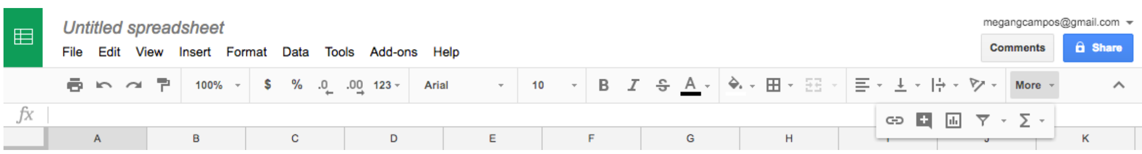
Google Sheets' "More" section

Given that the occasional user is likely working with the more basic functions—table construction, basic mathematic equations, and possibly chart creation—Sheets' mirroring of these functions in Excel works well with the mental model and semantic network that occasional users are likely to be able to successfully and quickly activate.

Expert users are perhaps the least likely to use Sheets. Though the more minimalistic toolbar might appeal to experts because they tend to rely on their mental model rather than instruction, the minimalism is not accompanied by the same or even similar functionality with regard to the complex interactions the expert is likely to expect from Excel. Experts likely use the highly complex, highly specialized functions available in Excel, many of which are absent or hidden in Sheets. Because the options available in the toolbar are significantly decreased (as opposed to simply minimized, which would likely be appealing), the expert would need to completely reconstruct several elements of their mental model to little functional benefit, and their schema recall and spreading activation might be either very slow or incorrect.



Excel's complex functionality toolbar



Google Sheets' minimized functionality toolbar

The significant adjustment from their complex mental model, as well as the decreased functionality in Sheets, makes the new program less suited to the needs of the expert user. The expert user is likely to remain with Excel, as it is itself their mental model and as a result they can use it quickly and accurately, minimizing confusion and frustration.

Conclusion

When creating a new interface, designers need to be mindful of the prior experiences of their users. Even if an interface is meant to be innovative, it needs to at least begin by introducing novel concepts through familiar channels so that users can quickly and accurately utilize the correct framework to understand how to interact with the interface. Sheets' design may be sufficient for current introductory purposes, but if the aim is to overtake Excel, Google needs to address design and functionality concerns that currently impact both novice and expert users.

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