

From Cognition to Computation:

A Comparative Review of Human Attention and Transformer Architectures

Minglu Zhao¹ Dehong Xu¹ Tao Gao²

Abstract

Attention is a cornerstone of human cognition that facilitates the efficient extraction of information in everyday life. Recent developments in artificial intelligence like the Transformer architecture also incorporate the idea of attention in model designs. However, despite the shared fundamental principle of selectively attending to information, human attention and the Transformer model display notable differences, particularly in their capacity constraints, attention pathways, and intentional mechanisms. Our review aims to provide a comparative analysis of these mechanisms from a cognitive-functional perspective, thereby shedding light on several open research questions. The exploration encourages interdisciplinary efforts to derive insights from human attention mechanisms in the pursuit of developing more generalized artificial intelligence.

1. Introduction

Over the past few years, the field of artificial intelligence (AI) has experienced a significant transformation with the introduction of the Transformer architectures, which have rapidly become the cornerstone of many state-of-the-art models in natural language processing (NLP), computer vision, and beyond. These architectures incorporate the concept of attention which echoes the complex cognitive process of human attention, a remarkable ability that enables us to focus on specific aspects of our environment while effectively filtering out extraneous information. Our review article aims to provide an in-depth comparative analysis of human attention and Transformer architectures, systematically examining the similarities and differences from various perspectives including vision, language, and agency.

Attention has been one of the most studied topics in

¹Department of Statistics, UCLA ²Department of Communication, UCLA. Correspondence to: Minglu Zhao <minglu.zhao@ucla.edu>.

Preprint. Work in progress.

cognitive psychology and influences a broad range of cognitive processes, contributing to perception, memory, and cognitive control. Classic studies in cognitive psychology have underlined attention's role as a filtering mechanism that selectively processes relevant information from the environment while managing cognitive resources (Broadbent, 1958; Treisman, 1964; Tanenhaus et al., 1995; Wolfe, 2000). Additionally, attention as a mental construct is intertwined with self-regulation and social communication processes, facilitating not only individuals' task commitment (Rueda et al., 2005; McClelland et al., 2007; Kanfer & Ackerman, 1989) but also cooperative interactions (Bratman, 1987; Tomasello et al., 1995). On the other hand, AI models with the notion of attention, exemplified by Transformer architectures, have shown great versatility and robustness in various applications. Initially designed for language processing, Transformer models have profoundly transformed the NLP landscape. By utilizing self-attention mechanisms to grasp the contextual relationships in sequences, they have made remarkable advancements in various tasks (Brown et al., 2020; OpenAI, 2023), including machine translation (Vaswani et al., 2017), sentiment analysis (Devlin et al., 2018), and text summarization (Liu & Lapata, 2019). In the computer vision domain, Transformer models have been applied to large-scale visual tasks and are able to capture long-range dependencies and hierarchies in image data (Dosovitskiy et al., 2020; Carion et al., 2020; Khan et al., 2022). Several recent architectures further incorporate Transformer architectures in decision-making tasks, treating decisions as a sequence generation task and thereby enabling the model to learn optimal action strategies based on past experiences (Chen et al., 2021; Janner et al., 2021; Meng et al., 2021).

The shared terminology of “attention” in human cognitive studies and Transformer architecture has given rise to intriguing parallels yet certain ambiguities concerning their relationship. Although both emphasize the selective processing of contextual information, human attention and the Transformer model present distinct disparities in their capacity constraints, attentional pathways, and intentional mechanisms. In this article, we systematically compare the two domains around these functional attributes. We note that this article does not serve as an exhaustive review of ei-

ther the human attention mechanism or the Transformer architecture, but rather a focused comparative analysis seeking to identify open directions for better incorporating insights from human attention to attention-based models in AI. We would also like to point out several reviews for a more comprehensive review of the topics (Wolfe, 2000; Carrasco, 2011; Khan et al., 2022; Guo et al., 2022).

2. Attention modeling and Transformer architecture

The principle of attention has been incorporated into various domains of AI, underpinning advancements in areas such as image recognition (Xu et al., 2015), speech recognition (Chorowski et al., 2015), and sequence-to-sequence prediction models (Bahdanau et al., 2014; Luong et al., 2015). However, in recognition of the significant impact it induced, this paper will concentrate on analyzing the Transformer architecture (Vaswani et al., 2017), a model that heavily relies on the attention mechanism. The Transformer is an innovative AI architecture and has been a game-changer in natural language processing which has laid the foundation for numerous state-of-the-art models. The Transformer model leverages self-attention mechanisms to capture contextual information in input sequences, making it highly effective in handling long-range dependencies while discarding the use of recurrence in the network.

Self-attention mechanism In essence, the Transformer architecture employs an “attention” mechanism that takes into account different words’ relevance in a sentence when processing each word. This approach can be compared to how we, as humans, selectively focus on certain aspects of a scene or conversation while tuning out the rest. Specifically, this is achieved through the self-attention mechanism, which computes the relationships between all pairs of elements in an input sequence. The core idea is to assign different weights to different elements based on their relevance to the current element being processed. The self-attention mechanism is defined as follows:

$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V, \quad (1)$$

where Q (query), K (key), and V (value) are derived from the input matrix X through linear transformations using weight matrices W^Q , W^K , and W^V : $Q = XW^Q$, $K = XW^K$, $V = XW^V$.

The keys (K), queries (Q), and values (V) in this formula can be thought of as abstractions that the Transformer uses to represent different aspects of the words in a sentence. The process of generating key (K) and query (Q) can be intuitively understood as the Transformer “asking questions”

about certain words (the queries) and “looking up answers” in other words (the keys). This “questioning” and “answering” process allows the Transformer to understand the interdependencies between words in a sentence. The relevance between one word’s key and another word’s query is computed by taking the dot product of the respective query and key (QK^T), which is a measure of their similarity. The softmax function transforms these relevance scores into probability values that sum up to one. $\sqrt{d_k}$ is a scaling factor that helps the model to be more trainable and stable. Values (V) are representations of the words themselves. After the Transformer computes the similarity between all queries and keys, it uses this information to weigh the importance of each value and creates a weighted sum of the values, which forms the output of the attention mechanism. In a way, values are the “content” that the Transformer wants to focus on, and the role of the keys and queries is to determine how much attention each value should be given.

Multi-head attention The multi-head attention mechanism in the Transformer model is a crucial step that allows the model to capture different aspects of the meaning of a sentence. Essentially, multi-head attention means running not one, but multiple attention mechanisms (or “heads”) in parallel, each focusing on different “types” or “aspects” of the input sequence’s information. This is defined in the following equations:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W^O, \quad (2)$$

where each attention head is computed as:

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V). \quad (3)$$

Each attention head applies the attention mechanism but with different learned linear transformations (i.e., different weight matrices W_i^Q , W_i^K , W_i^V). Because these transformations are different for each head, each head learns to pay attention to different features in the input. After all the attention heads have processed the input sequence independently, the results from each head are concatenated and then linearly transformed using another learned weight matrix W^O . This step integrates the different “perspectives” from each head into a unified representation, which is then passed onto the next layer in the Transformer model.

3. Comparative analysis of human attention and attention in Transformers

We structure our review around key functions of attention as understood from a cognitive perspective and distinguish

these based on their similarities or differences when comparing human attention to the Transformer architecture. We outline a series of influential studies in cognitive science regarding the idea of human attention, from domains including vision, language, and agency. We further list out some recent work built on top of the Transformer architecture for comparison.

3.1. Similarities

3.1.1. SELECTIVE ATTENTION

From a functional perspective, human attention mechanism can be considered a selective process which allows us to focus on a particular object or task while filtering out irrelevant or distracting information. This phenomenon is often described as the “cocktail party effect,” referring to our ability to concentrate on a single conversation amidst a noisy environment (Cherry, 1953). Broadbent’s Filter Model further suggested that humans tend to focus on specific elements while filtering out others (Broadbent, 1958). The Attenuation Model by Treisman modified this understanding by proposing that unattended information is not completely filtered out, but rather “turned down” or attenuated (Treisman, 1964). Later, (Deutsch & Deutsch, 1963) suggested that the selection of relevant stimuli happens later in the processing chain, indicating selective attention operates not only on the perceptual level. Several lines of work deepened this understanding through researching on spatial attention, where humans filter out spatially nearby distractors for efficient information processing (Eriksen & Eriksen, 1974; Posner, 1980)

Similarly, the Transformer model applies a form of selective attention to process sequences of data (Vaswani et al., 2017). Through its self-attention mechanism, the Transformer model calculates attention scores, or weights, for each element in the input relative to all others. The computation of these weights is managed by a *softmax* function, designed such that higher weights are allocated to larger input values, while ensuring that the aggregate of all weights sums up to one. In this way, if certain parts receive a higher attention score, the remaining elements are accordingly assigned a smaller fraction of the attention. The mechanism thus allow the Transformer to focus more on some and less on others, echoing how humans tend to concentrate on some inputs while neglecting others.

3.1.2. CONTEXTUAL UNDERSTANDING

Humans typically interpret sensory inputs within their broader context, both in visual scenes and linguistic utterances, a feature commonly referred to as contextual processing. A series of studies demonstrated the effect of context on object recognition (Palmer, 1975). When an object is presented in a congruent scene (e.g., a loaf of bread in a

kitchen), people recognize it more quickly and accurately than when it is in an incongruent scene (e.g., a loaf of bread on a beach). A similar effect was found in linguistics studies, where researchers showed that when listeners hear an ambiguous word, they do not perceive both meanings and then select the appropriate one; instead, they immediately interpret the word in light of the surrounding sentence context (Tanenhaus et al., 1995). This suggests that context is integrated in real time during language comprehension. In studies on human decision-making, researchers revealed how the phrasing of a problem can drastically change people’s decisions, even when the underlying objective information is the same. For instance, people may opt for a surgery when told it has a 90% survival rate, but reject it when told it has a 10% mortality rate, illustrating how our decisions are shaped by the context in which information is presented (Tversky & Kahneman, 1981). In this way, humans’ interpretation of sensory stimuli is informed not only by the immediate properties of the stimuli themselves, but also by their surroundings.

With a similar idea, the Transformer model is designed to accommodate context in processing sequences of data. This is often regarded as one of the major reasons why Transformer models are competitive in multiple domains. Specifically, the self-attention mechanism considers the entire input sequence when processing each token. This design enables the model to accurately capture long-range dependencies in the data, enriching the representation of each token by incorporating the context provided by all other tokens in the sequence (Vaswani et al., 2017). This design is particularly powerful in tasks such as machine translation and text summarization, where understanding the contextual relationships within the input sequence is critical (Vaswani et al., 2017). Recent work further take advantage of this design and apply Transformers to sequential decision making tasks, where the action-to-taken is dependent on the context of past experience (Chen et al., 2021; Meng et al., 2021).

3.2. Differences

3.2.1. CAPACITY CONSTRAINTS

One salient distinction between human attention and Transformer models comes from their capacity constraints. The human attention system operates within constraints defined by perceptual and cognitive boundaries, including a limited visual field and working memory capacity (Broadbent, 1958; Cowan, 2001). These biological constraints necessitate the deployment of attention to prioritize and extract relevant information. The spotlight of human attention, therefore, shifts and scales based on task demands and environmental cues, enabling efficient processing within these capacity constraints (Carrasco, 2011). The capacity

constraint of human attention has been extensively investigated in psychological studies particularly in visual attention. Starting with Broadbent's Filter Model (Broadbent, 1958), it was proposed that human attention serves as a bottleneck that allows only certain information to pass for further processing due to limited capacity. Researchers further introduced the concept of "selective looking", showing that when engaged in a demanding task, observers can fail to notice unexpected events (Neisser & Becklen, 1975). In the famous Invisible Gorilla Experiment (Simons & Chabris, 1999), participants watched a video where they were asked to count basketball passes. During the video, a person in a gorilla suit walked through the scene. Despite the conspicuousness of the event, half of the participants failed to notice the gorilla, illustrating the limits of human attention capacity and the phenomenon of inattentional blindness. The Load Theory of attention also suggested that the level of perceptual load in a task determines the efficiency of selective attention (Lavie, 2005). The capacity constraint is also evident in the visual search tasks, where humans' attentional capacity is guided by feature-based and spatial-based information (Wolfe & Gray, 2007). From this perspective, human attention is indeed a double-edged sword: while it facilitates the extraction of needed information from a plethora of sensory input, while simultaneously imposing limits on what can be attended to at any one time (Broadbent, 1958; Lavie, 2005). Moreover, due to the limited capacity of our cognitive resources, human attention typically operates in a sequential manner, focusing on a restricted set of inputs at any given moment and necessitating constant shifts to process diverse environmental elements (Broadbent, 1958; Dux et al., 2006).

In contrast, Transformer architectures, being artificial constructs, do not possess these inherent biological constraints. Given adequate computational resources, they can process all parts of the input in parallel, regardless of the input's size or complexity (Vaswani et al., 2017). This parallel processing capability enables Transformers to consider all elements simultaneously, capturing dependencies and relationships across the entire sequence without the need to sequentially shift focus as in human attention. Thus, attention in Transformers can be viewed as a mechanism that enables the model to extract contextual relationships within the data, rather than a solution to a processing limitation.

3.2.2. ATTENTION PATHWAYS

Human attention is characterized by a dynamic interplay between top-down and bottom-up processes (Corbetta & Shulman, 2002). Top-down attention is goal-directed and driven by cognitive factors like knowledge and expectations. It allows us to selectively focus on information that is relevant to our current task or intention. This idea is evident in neuroscience studies, where

researchers found that top-down influences bias neural representation towards task-relevant information amidst competing stimuli (Desimone & Duncan, 1995). There is also enhanced sensory activity when anticipating a target stimulus, thus underscoring the priming effect of top-down attention (Egner & Hirsch, 2005). From an agency perspective, the top-down attention enables humans to employ various heuristics, achieving more efficient decision-making by directing attention towards relevant or expected stimuli (Tversky & Kahneman, 1974). On the other hand, bottom-up attention is stimulus-driven and automatic, which is primarily guided by salient stimuli in the environment, such as bright colors, loud noises, or sudden movements (Itti & Koch, 2001; Chun et al., 2011). This type of attention helps us quickly identify potential threats or opportunities in our surroundings without the need for conscious control (Yantis, 1998). Together, human attention is indeed a dual-pathway mechanism with top-down control guiding the focus of attention, while bottom-up signals determining instant attention shifts (Buschman & Miller, 2007).

In contrast to human attention, attention allocation in Transformer models is an entirely data-driven process. The attention weights within these models are learned during the training phase, based solely on the input data (Vaswani et al., 2017). This design paradigm is limited to one direction of information processing, wherein the model aggregates lower-level features to construct higher-level, semantically rich representations. Consequently, the attention focus within Transformers is shaped purely by previous learning experiences, as opposed to the intricate interplay of cognitive factors observed in humans (Corbetta & Shulman, 2002).

3.2.3. INTENTIONAL NATURE

In this section, we compare the intentional nature of attention in humans and the Transformers architecture. For humans, the attention mechanism is not solely a passive response to limited cognitive resources, but also a deliberate, controlled process. The process of allocating attention is an active decision-making mechanism, reflecting an individual's agency in consciously directing their cognitive resources in alignment with their beliefs, goals, and intentions, in line with Theory of Mind (Bratman, 1987). The ability to intentionally ignore extraneous information and focus on achieving one's goal is critical to human decision-making. Effective self-regulation of attention plays a crucial role in sustaining commitment to tasks (Rueda et al., 2005; McClelland et al., 2007), especially for those requiring prolonged effort, such as complex problem-solving and learning (Kanfer & Ackerman, 1989; Muraven & Baumeister, 2000), as well as in tasks where multiple outcomes are desirable (Cheng et al., 2022).

Furthermore, attention is a mental construct that significantly contributes to effective communication by serving as a crucial signal for interpreting human intention, emotion, and personality, often indicated by eye gaze. This nonverbal cue provides insightful information into an individual's thoughts and focus. Evolutionarily, humans have uniquely developed a high color contrast between the white sclera and the colored iris, unlike chimpanzees, facilitating discernment of gaze direction and, subsequently, intention and emotions (Kobayashi & Kohshima, 1997; Tomasello et al., 2007). This visibility of human eye gaze communicates our attention and intention nonverbally with impressive efficacy. Humans, even at a young age, are highly sensitive to the gaze direction of others, enabling an understanding of the intentions and mental states of the person they are interacting with (Hood et al., 1998; Tomasello et al., 1995). This sensitivity to gaze direction often culminates in gaze alternation between the object of interest and the communication partner, signalling an intention to share attention, thereby inviting social interaction (Tomasello et al., 2005). Critically, such shared attention underpins various social interactions and is instrumental in the development of language, social cognition, and theory of mind. Hence, attention operates as a vital component of social cognition by shaping our understanding of each other's intentions.

On the other hand, although the determination of focus in Transformers depends on the learned attention weights, which resonates with the idea of a controlled process as in human attention allocation, it is crucial to note that the Transformer architecture does not possess inherent cognitive states. The concept of "attention" within this context is essentially a mathematical construct based on learned data patterns. It remains unclear whether the representations output from the attention mechanism coincides with what one believes to be important from an agency perspective.

4. Potential Directions

Drawing upon the comparative analysis of human attention and attention in the Transformer architecture presented thus far, we now turn our focus to identifying salient open research questions. The objective is to explore the extent to which principles of human attention can guide the modeling of attention in artificial intelligence. Specifically, we would like to note that not all characteristics of the human attention mechanism may be desirable when translated into the artificial intelligence domain. Careful judgement is thus required to integrate only those characteristics of human attention that are beneficial in the context of artificial intelligence while avoiding potential impediments.

4.1. Is emulating human capacity constraints beneficial?

Humans possess a limited capacity for cognitive resources including a limited visual field and working memory capacity (Broadbent, 1958; Cowan, 2001). These limitations necessitate the need for attention as a cognitive tool that selectively processes information based on its importance. In contrast, Transformer architectures do not face such limitations and handle large volumes of data simultaneously. Despite the disparity, it is important to note that the absence of capacity constraints in Transformers does not denote a deficiency. In fact, one of the Transformer's crucial strengths lies in its ability to process large amount of information in parallel, which has proven critical in recent large-scale models like GPT (Brown et al., 2020; OpenAI, 2023). Such models have demonstrated impressive performance across a wide range of tasks by leveraging their capacity to parse and process massive corpora of textual data. This computational efficiency is indispensable for AI to effectively aid humans in various fields, such as autonomous driving, where it is crucial to augment human capabilities and overcome cognitive limitations.

4.2. How can models adopt a resource-rational approach from human attention?

From another perspective, while the Transformer architecture is not bounded by the same cognitive resource limitations as humans, they may still glean invaluable insights from understanding the efficiency with which humans allocate and utilize their limited resources. From a resource-rational perspective (Griffiths et al., 2015; Lieder & Griffiths, 2020), human cognition demonstrates an important optimization between performance and resource allocation that allows us to operate effectively in complex environments despite our cognitive constraints. Although recent developments in large language models (LLMs) have reached great success, training of the models typically demand substantial computational resources (Brown et al., 2020; OpenAI, 2023). Unlike humans, who can generate near-instantaneous responses to diverse stimuli, these models require significant computation to produce comparable outputs. Hence, the challenge remains for AI researchers: to maximize efficiency rather than to merely increase capacity. Such economical use may thus pave the way for the development of more robust, effective, and resource-friendly models.

4.3. How can attention modeling generate meaningful representations?

Human attention comes with inherent cognitive limitations. This is evident in phenomena such as inattentional blindness (Simons & Chabris, 1999) and change blindness

(Rensink et al., 1997), wherein humans overlook certain aspects of a visual scene. Beyond indicating a limitation, these phenomena indeed highlight humans’ ability to discern the semantically significant components within a complicated visual scene. The human visual attention system does not construct an exhaustive, detailed representation of the visual world; rather, it selects and processes only the crucial segments (Treisman & Gelade, 1980; Treue, 2003). This capacity for discernment underscores the impressive human capability to extract meaningful information from inputs, thereby crafting a useful representation. Contrarily, models like Transformers treat processing as a predominantly data-driven operation, and thus whether the preserved representation is semantically meaningful is still an opaque question that relies on subjective judgements. To develop more generalizable AI algorithms, meaningful representation of one’s attention could serve as a critical component to make AI more interpretable and thus trustworthy (Doshi-Velez & Kim, 2017).

4.4. How can attention be formulated as an explicit component of agency?

Beyond a functional construct of human perception, attention further serves as a key element of human agency that can be intentionally modulated and controlled. At an individual level, it operates as a self-regulation mechanism to shield us from irrelevant and distracting information (Kanfer & Ackerman, 1989; Muraven & Baumeister, 2000). In social interactions, attention functions as a conduit for understanding the intentions of others and facilitating communication (Bratman, 1987). Research in cognitive psychology indicates that joint attention serves as the foundation of human cooperation, forming a shared commitment to a task (Tomasello et al., 2005; Tang et al., 2020; 2022). Indeed, theories suggest that the primary objective of conversation is to manipulate each other’s attention, thereby fostering a shared common ground of information among cooperative agents (Stacy et al., 2020; 2021; Fan et al., 2021). In this way, attention extends beyond merely representing an individual’s focus; it serves as an external and explicit construct intertwined with one’s agency and implies a more profound role in mediating human interactions and shaping social dynamics. On the other hand, although recent studies incorporating the Transformer-based architecture have emphasized learning from past experiences to decide on action strategies (Chen et al., 2021; Janner et al., 2021), attention in these models primarily serves to calculate the relationship between all pairs of elements in the input sequence, rather than functioning as a mental mechanism to generate intentional behavior. The concept of joint attention, central to human cooperation from a cognitive science perspective, is not explicitly incorporated in recent developments of

multi-agent algorithms based on Transformers (Meng et al., 2021; Wen et al., 2022). As a result, it remains an open question how we can more effectively incorporate the human perspective of attention into AI models.

5. Conclusion

In conclusion, our review drew a comparison between the human attention mechanism and the Transformer architecture, revealing a diverse range of similarities and differences. We hope the analysis can serve to highlight areas where artificial intelligence might draw inspiration from the intricacies of human attention while also keeping the unique strengths of Transformer-based models.

References

- Bahdanau, D., Cho, K., and Bengio, Y. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*, 2014.
- Bratman, M. Intention, plans, and practical reason. 1987.
- Broadbent, D. E. *Perception and communication*. Pergamon Press, 1958.
- Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.
- Buschman, T. J. and Miller, E. K. Top-down versus bottom-up control of attention in the prefrontal and posterior parietal cortices. *science*, 315(5820):1860–1862, 2007.
- Carion, N., Massa, F., Synnaeve, G., Usunier, N., Kirillov, A., and Zagoruyko, S. End-to-end object detection with transformers. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part I 16*, pp. 213–229. Springer, 2020.
- Carrasco, M. Visual attention: The past 25 years. *Vision research*, 51(13):1484–1525, 2011.
- Chen, L., Lu, K., Rajeswaran, A., Lee, K., Grover, A., Laskin, M., Abbeel, P., Srinivas, A., and Mordatch, I. Decision transformer: Reinforcement learning via sequence modeling. *Advances in neural information processing systems*, 34:15084–15097, 2021.
- Cheng, S., Zhao, M., Zhu, J., Zhou, J., Shen, M., and Gao, T. Intentional commitment through an internalized theory of mind: Acting in the eyes of an imagined observer. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, volume 44, 2022.

- Cherry, E. C. Some experiments on the recognition of speech, with one and with two ears. *The Journal of the acoustical society of America*, 25(5):975–979, 1953.
- Chorowski, J. K., Bahdanau, D., Serdyuk, D., Cho, K., and Bengio, Y. Attention-based models for speech recognition. *Advances in neural information processing systems*, 28, 2015.
- Chun, M. M., Golomb, J. D., and Turk-Browne, N. B. A taxonomy of external and internal attention. *Annual review of psychology*, 62:73–101, 2011.
- Corbetta, M. and Shulman, G. L. Control of goal-directed and stimulus-driven attention in the brain. *Nature reviews neuroscience*, 3(3):201–215, 2002.
- Cowan, N. The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and brain sciences*, 24(1):87–114, 2001.
- Desimone, R. and Duncan, J. Neural mechanisms of selective visual attention. *Annual review of neuroscience*, 18(1):193–222, 1995.
- Deutsch, J. A. and Deutsch, D. Attention: Some theoretical considerations. *Psychological review*, 70(1):80, 1963.
- Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
- Doshi-Velez, F. and Kim, B. Towards a rigorous science of interpretable machine learning. *arXiv preprint arXiv:1702.08608*, 2017.
- Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020.
- Dux, P. E., Ivanoff, J., Asplund, C. L., and Marois, R. Isolation of a central bottleneck of information processing with time-resolved fmri. *Neuron*, 52(6):1109–1120, 2006.
- Egner, T. and Hirsch, J. Cognitive control mechanisms resolve conflict through cortical amplification of task-relevant information. *Nature neuroscience*, 8(12):1784–1790, 2005.
- Eriksen, B. A. and Eriksen, C. W. Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & psychophysics*, 16(1):143–149, 1974.
- Fan, L., Qiu, S., Zheng, Z., Gao, T., Zhu, S.-C., and Zhu, Y. Learning triadic belief dynamics in nonverbal communication from videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 7312–7321, 2021.
- Griffiths, T. L., Lieder, F., and Goodman, N. D. Rational use of cognitive resources: Levels of analysis between the computational and the algorithmic. *Topics in cognitive science*, 7(2):217–229, 2015.
- Guo, M.-H., Xu, T.-X., Liu, J.-J., Liu, Z.-N., Jiang, P.-T., Mu, T.-J., Zhang, S.-H., Martin, R. R., Cheng, M.-M., and Hu, S.-M. Attention mechanisms in computer vision: A survey. *Computational Visual Media*, 8(3):331–368, 2022.
- Hood, B. M., Willen, J. D., and Driver, J. Adult’s eyes trigger shifts of visual attention in human infants. *Psychological Science*, 9(2):131–134, 1998.
- Itti, L. and Koch, C. Computational modelling of visual attention. *Nature reviews neuroscience*, 2(3):194–203, 2001.
- Janner, M., Li, Q., and Levine, S. Offline reinforcement learning as one big sequence modeling problem. *Advances in neural information processing systems*, 34:1273–1286, 2021.
- Kanfer, R. and Ackerman, P. L. Motivation and cognitive abilities: An integrative/aptitude-treatment interaction approach to skill acquisition. *Journal of applied psychology*, 74(4):657, 1989.
- Khan, S., Naseer, M., Hayat, M., Zamir, S. W., Khan, F. S., and Shah, M. Transformers in vision: A survey. *ACM computing surveys (CSUR)*, 54(10s):1–41, 2022.
- Kobayashi, H. and Kohshima, S. Unique morphology of the human eye. *Nature*, 387(6635):767–768, 1997.
- Lavie, N. Distracted and confused?: Selective attention under load. *Trends in cognitive sciences*, 9(2):75–82, 2005.
- Lieder, F. and Griffiths, T. L. Resource-rational analysis: Understanding human cognition as the optimal use of limited computational resources. *Behavioral and brain sciences*, 43:e1, 2020.
- Liu, Y. and Lapata, M. Text summarization with pretrained encoders. *arXiv preprint arXiv:1908.08345*, 2019.
- Luong, M.-T., Pham, H., and Manning, C. D. Effective approaches to attention-based neural machine translation. *arXiv preprint arXiv:1508.04025*, 2015.

- McClelland, M. M., Cameron, C. E., Connor, C. M., Farris, C. L., Jewkes, A. M., and Morrison, F. J. Links between behavioral regulation and preschoolers' literacy, vocabulary, and math skills. *Developmental psychology*, 43(4): 947, 2007.
- Meng, L., Wen, M., Yang, Y., Le, C., Li, X., Zhang, W., Wen, Y., Zhang, H., Wang, J., and Xu, B. Offline pre-trained multi-agent decision transformer: One big sequence model conquers all starcraftii tasks. *arXiv preprint arXiv:2112.02845*, 2021.
- Muraven, M. and Baumeister, R. F. Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychological bulletin*, 126(2):247, 2000.
- Neisser, U. and Becklen, R. Selective looking: Attending to visually specified events. *Cognitive psychology*, 7(4): 480–494, 1975.
- OpenAI. Gpt-4 technical report. *arXiv*, 2023.
- Palmer, t. E. The effects of contextual scenes on the identification of objects. *Memory & cognition*, 3(5):519–526, 1975.
- Posner, M. I. Orienting of attention. *Quarterly journal of experimental psychology*, 32(1):3–25, 1980.
- Rensink, R. A., O'regan, J. K., and Clark, J. J. To see or not to see: The need for attention to perceive changes in scenes. *Psychological science*, 8(5):368–373, 1997.
- Rueda, M. R., Posner, M. I., and Rothbart, M. K. The development of executive attention: Contributions to the emergence of self-regulation. *Developmental neuropsychology*, 28(2):573–594, 2005.
- Simons, D. J. and Chabris, C. F. Gorillas in our midst: Sustained inattentional blindness for dynamic events. *perception*, 28(9):1059–1074, 1999.
- Stacy, S., Zhao, Q., Zhao, M., Kleiman-Weiner, M., and Gao, T. Intuitive signaling through an "Imagined We". In *CogSci*, 2020.
- Stacy, S., Li, C., Zhao, M., Yun, Y., Zhao, Q., Kleiman-Weiner, M., and Gao, T. Modeling communication to coordinate perspectives in cooperation. *arXiv preprint arXiv:2106.02164*, 2021.
- Tanenhaus, M. K., Spivey-Knowlton, M. J., Eberhard, K. M., and Sedivy, J. C. Integration of visual and linguistic information in spoken language comprehension. *Science*, 268(5217):1632–1634, 1995.
- Tang, N., Stacy, S., Zhao, M., Marquez, G., and Gao, T. Bootstrapping an imagined we for cooperation. In *Proceedings of the Annual Meeting of the Cognitive Science Society (CogSci)*, 2020.
- Tang, N., Gong, S., Zhao, M., Gu, C., Zhou, J., Shen, M., and Gao, T. Exploring an imagined "we" in human collective hunting: Joint commitment within shared intentionality. In *Proceedings of the annual meeting of the cognitive science society*, volume 44, 2022.
- Tomasello, M., Carpenter, M., Call, J., Behne, T., and Moll, H. Understanding and sharing intentions: The origins of cultural cognition. *Behavioral and brain sciences*, 28(5): 675–691, 2005.
- Tomasello, M., Hare, B., Lehmann, H., and Call, J. Reliance on head versus eyes in the gaze following of great apes and human infants: the cooperative eye hypothesis. *Journal of human evolution*, 52(3):314–320, 2007.
- Tomasello, M. et al. Joint attention as social cognition. *Joint attention: Its origins and role in development*, 103130:103–130, 1995.
- Treisman, A. Monitoring and storage of irrelevant messages in selective attention. *Journal of Verbal Learning and Verbal Behavior*, 3(6):449–459, 1964.
- Treisman, A. M. and Gelade, G. A feature-integration theory of attention. *Cognitive psychology*, 12(1):97–136, 1980.
- Treue, S. Visual attention: the where, what, how and why of saliency. *Current opinion in neurobiology*, 13(4):428–432, 2003.
- Tversky, A. and Kahneman, D. Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, 185(4157):1124–1131, 1974.
- Tversky, A. and Kahneman, D. The framing of decisions and the psychology of choice. *science*, 211(4481):453–458, 1981.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.
- Wen, M., Kuba, J., Lin, R., Zhang, W., Wen, Y., Wang, J., and Yang, Y. Multi-agent reinforcement learning is a sequence modeling problem. *Advances in Neural Information Processing Systems*, 35:16509–16521, 2022.
- Wolfe, J. M. Visual attention. *Seeing*, pp. 335–386, 2000.
- Wolfe, J. M. and Gray, W. Guided search 4.0. *Integrated models of cognitive systems*, pp. 99–119, 2007.
- Xu, K., Ba, J., Kiros, R., Cho, K., Courville, A., Salakhudinov, R., Zemel, R., and Bengio, Y. Show, attend and

tell: Neural image caption generation with visual attention. In *International conference on machine learning*, pp. 2048–2057. PMLR, 2015.

Yantis, S. Control of visual attention. *attention*, 1(1):223–256, 1998.