Creative Captioning: An AI Grand Challenge Based on the Dixit Board Game

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Abstract

We propose a new class of “grand challenge” AI problems that we call creative captioning—generating clever, interesting, or abstract captions for images, as well as understanding such captions. Creative captioning draws on core AI research areas of vision, natural language processing, narrative reasoning, and social reasoning, and across all these areas, it requires sophisticated uses of common sense and cultural knowledge. In this paper, we analyze several specific research problems that fall under creative captioning, using the popular board game Dixit as both inspiration and proposed testing ground. We expect that Dixit could serve as an engaging and motivating benchmark for creative captioning across numerous AI research communities for the coming 1-2 decades.

Introduction

Consider the images in Figure 1. For each of the following phrases, which image do you think is being described?

1. A person on a tall ladder using a hammer and chisel to make a cloud pigeon in the sky, plus a cloud butterfly.
2. A difficult choice among three options.
3. Scary.
4. Monty Hall.
5. She got the little dog, too!

Phrase 1 is fairly easy to match; it is just a literal description of the contents of Image F.

Phrase 2 is a little bit harder; it does not use any specific nouns that refer to depicted objects, but it does refer to “three options,” which suggests the three doors in Image D. Nothing in Image D directly indicates that the choice is a difficult one, or really that there is a “choice” at all, but we can easily imagine that the knightly rabbit is facing a choice.

Phrase 3 is harder still—“scary” refers to an emotional quality, and so we have to consider the affect or mood conveyed by each image. (The authors find Image A to be the most scary, though E is admittedly also creepy, especially if one has botanophobia, or fear of plants!)

Phrase 4 requires know who (or what) Monty Hall is. Among AAAI readers, we expect that at least a few will recognize our reference to the famous Monty Hall problem of choosing a prize from behind three closed doors (Selvin\(^{1975\text{a, b}}\)), thus referring again to Image D.

We leave Phrase 5 as an exercise for the reader. (Hint: This involves cultural reference to the classic American film The Wizard of Oz, and both a song and a dialogue from it.)

We define creative captioning as a class of problems that includes (a) generating clever, interesting, or abstract captions for images (as we did in creating our list of phrases), and (b) understanding such captions (as you did in matching each phrase to an image), and related variants thereof.

Our work is inspired by the popular board game Dixit (Roubira\(^{2008}\)), in which players both generate and try to
match “interesting” captions to rather surreal-looking images, like those shown in Fig. 1.

While Dixit provides one concrete instantiation of problems involved in creative captioning, other examples include the well-known New Yorker cartoon captioning contest (Prince and Radev 2017; Bogert, Watson, and Schecter 2020; Li 2020), or generating engaging titles for inventions (Senda, Sinohara, and Okumura 2004) or artwork.

Creative captioning is very related to image captioning (Hossain et al. 2019), though it goes beyond to incorporate more sophisticated aspects of vision (e.g., multiple and often abstract interpretations of an image), natural language processing (including idioms, cultural references, etc.), story or narrative reasoning (e.g., inferring, or imagining, narrative constructs related to a given image or phrase), and social reasoning (such as thinking about the intended audience for a caption). Contributions of this paper include:

- We identify characteristics that make Dixit a fascinating window into human intelligence, by reviewing Dixit-related research in psychology and education.
- We describe how the Dixit board game could be set up as an AI challenge, including specific assumptions, game variants, and evaluation methods.
- We analyze the suite of problems that an artificial agent faces while playing Dixit, and we review the state of the art in AI research related to each problem.

The Dixit Game

Dixit (Roubira 2008) is a tabletop card game typically played with 4-6 players. The game contains 84 cards, 36 numbered tokens, 6 player markers, and a game board. Cards are storybook-style illustrations, often surreal (Figure 1). Game play takes place as follows (Figure 2).

Setup. Each player starts with zero points. The deck is shuffled, and each player is dealt six cards. Each player also receives tokens to be used for voting. A player is selected at random to be the first storyteller.

Storyteller Turn. At the beginning of each round, the storyteller secretly selects a card from their hand. They then utter a clue or label for the card, and place their card face down on the table. Per the Dixit instructions:

“[This] clue can take many different forms: it can be made up of one or more words or can even be a sound or group of sounds that represent the clue. It can be invented on the spot or it can take the form of already existing works (a part of a poem or song, a movie title, a proverb, etc...)” (Roubira 2008).

Remaining Players’ Turn. Then, each remaining player picks a “decoy” card from their own hand that they associate with the storyteller’s utterance. These cards are placed face down on top of the storyteller’s card.

Voting. After all players have added their cards to the pile, the storyteller shuffles and then reveals all of the cards. Each player, other than the storyteller, then votes for the card that they believe to be the storyteller’s by placing the corresponding token face down in front of them. (Tokens are placed face-down so that votes are hidden while players are still making decisions.) Players cannot vote for their own card.

Scoring. Each round’s point distribution is determined by the players’ votes. If all players or no players correctly guessed the storyteller’s card, the storyteller does not earn any points, and all other players earn 2 points. Otherwise, the storyteller earns 3 points, as does each player that guessed correctly. Each player, other than the storyteller, earns 1 additional point for each vote that their own card received.

Next Turn. All players draw from the deck to replenish their hand back up to six cards. The storyteller role is passed clockwise.

Game ending. The game ends once any player has reached 30 points or when the last card has been drawn from the deck, at which time the player with the most points wins.

Dixit as creative captioning. Dixit involves multiple forms of creative captioning, including when the storyteller chooses a card and generates a clue/phrase for it; when the other players select their own decoy cards; and when players vote on the card they think is the original storyteller’s card.
Table 1: Sampling of research studies using Dixit from psychology, education, and other social and cognitive science areas.

| Reference            | Summary                                                                 | Details                                                                                                                                                                                                 |
|----------------------|------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Piccolo & Guerra 2010 | Used Dixit to help students learn about design patterns in programming. | Asked 19 graduate computing students in Brazil to play Dixit but with allowable phrases only relating to design patterns and concepts in object-oriented design. Majority of students liked activity and felt that it enhanced their learning. |
| Chircop 2016         | Proposed a typology for board games including rules, randomness, theme, and interaction. | Mentions Dixit as an example of a game with low rule complexity. Also discusses how in storytelling games, player-generated input forms a significant part of gameplay, though this input is still constrained by game rules and also by social norms. |
| Mousnier et al. 2016 | (In French.) Description of using Dixit cards during therapy.           | Use Dixit cards for therapy to elicit metaphorical language and thought. Describe several sessions with various patients, in which Dixit cards were used. Patients chose cards in response to a question (e.g., “How do you feel?”) and then discussed, based on prompts from the examiners. |
| Bekesas et al. 2018  | Used a game similar to Dixit for eliciting people’s sociocultural knowledge and identity | Created a new game based off a popular Brazilian game, and inspired by Dixit and others, to elicit people’s “cultural repertoire” and also the personal meanings or interpretations they bring. Successfully tested with 170 youth in Brazil aged 12-24 years. |
| Vitancol & Baria 2018 | Evaluated how group communication changed over the course of playing Dixit. | Had visitors to a boardgame cafe play Dixit. Rated players qualitatively on their level of Participation, Observation, Evaluation, and Adaptation. Found that communication increased throughout gameplay. |
| Musat & Fallings, 2013 | Created a human computation game for AI evaluation, loosely based on Dixit | Created a game, loosely based on Dixit rules, for human analysis of AI sentiment analysis. Present a pilot study, showing that people understand the game and that system’s error type affects peoples’ descriptions. |
| Vayanou et al. 2019  | Used Dixit-style game to help people engage with visual art.             | Conducted a series of group sessions with adults playing a Dixit-like game to tell stories about visual artworks, either in museum exhibitions or at home. Participant observations indicated increased engagement, meaning-making, and interest in artworks. |

Research on Dixit with People

Dixit (or Dixit-inspired activities) represents a fascinating task format for eliciting human creative captioning, as evidenced by its widespread use in a variety of research studies across different fields. Table 1 lists a sampling of these studies. For example, one study used a card game similar to Dixit as a research tool for querying people’s cultural knowledge (Bekesas et al. 2018).

In another quite clever deployment of the game, Dixit was used to teach software design patterns to graduate CS students. Essentially, students played Dixit as usual except that their “clues” had to be drawn from the vocabulary of programming design patterns taught during the course. As an example from this study (Piccolo and Guerra 2010):

“In his turn, a player select in his hand a card that has a humanized rabbit looking for three different doors. He thinks that this card relates to the Strategy pattern, where you can choose different implementations for an algorithm. Then, he put his card backwards in the table, saying “Strategy”. Each other player them should select the card in his hand that he thinks that is the most related to the Startegy pattern. For instance, another player should select a card with several water drops, relating that in the Strategy pattern there are several classes encapsulated in the same abstraction.”

Other studies include using Dixit as part of board game training to make people smarter (Bartolucci, Mattioli, and Batinj 2019); analyzing Dixit within a taxonomy of narrative board and card games (Sullivan and Salter 2017); discussing Dixit as an adaptation of Rorschach tests (Rogerson and Cocks 2017); using Dixit cards to spur ideation for game design (Wetzel, Rodden, and Benford 2017); using Dixit cards as a method for language sampling in children that elicits more lexical diversity than traditional methods (Smith 2018); Dixit as edutainment (Novikova and Beskrovnyaya 2015); how Dixit can be used to teach complex concepts like ethics (Mazurkiewicz 2013); discussions of the shared narrative experience among players of games like Dixit (Montanarini 2019); and using Dixit for therapy (Ikiz and Béziat 2020).

Dixit AI Challenge

While the rules of Dixit are easy to follow, we believe that the game will pose a significant challenge to modern AI agents. As such, we propose Dixit as a creative captioning AI challenge under the following parameters. (We use the abbreviation DA to refer to a Dixit Agent.)

We note that there are two ways to evaluate a DA: winning the game and playing it in a believably human-like way. However, omitting the latter requirement changes the game considerably, in that human players would then be voting and acting based on their own mental models of how they think an artificial agent would be playing the game. Thus, our proposed Dixit AI challenge assumes that human players do not know which is the artificial agent (or perhaps that there is an artificial agent at all).

1. The DA must be able to play a full Dixit game against human players. That is, it must be able to play both storyteller and non-storyteller roles.
2. The basic Dixit game is intended for 4-6 human players, and thus the DA must be able to play against anywhere from 3-5 human players.
3. While the official rules of Dixit allow for game phrases to include “noises” or, in some variants, physical gestures or charades, the proposed AI challenge will allow only text-based phrases.
4. Dixit calls for game phrases to be “short.” We propose
imposing a hard limit \( K \) on phrase length as a game parameter. For example \( K = 4 \) would be quite reasonable.

5. The game will be played over a virtual connection, such that the only communications among players consists of selections of cards, plain-text phrases, and votes. Thus, we eliminate the roles of facial expressions, body language, prosody, and other forms of nonverbal communication. (Perhaps we leave these for the next AI Dixit challenge!)

6. Table chatter is not permitted amongst players, i.e., there is no extraneous conversation allowed.

7. The game will take place using a specified language (e.g., English), cultural context (e.g., the United States), and player characteristics (e.g., adults, or college students, or 10-year-olds, or college computer science students, etc.). We expect that DAs will be designed initially for one specific set of these characteristics, but the core AI methods developed ought to (eventually) be able to generalize across these different game contexts.

8. The human players should be strangers to each other; this ensures that the players are not relying on personal knowledge, inside jokes, etc., that would be impossible for the DA to know or understand. However, the DA and human players may well observe and learn from each other’s behaviors during the course of the game.

9. The game will be played with previously unseen cards (e.g., from an expansion pack) that neither the DA nor any of the players have previously seen.

10. The DA must be able to explain all of its actions (i.e., why it selected a phrase or card), This is to prevent winning by way of Eliza effect (O’Dell and Dickson 1984), and is a reasonable requirement to apply to human players as well.

We intend for these parameters to limit the difficulty of the game, while maintaining its spirit. For example, while table chatter adds entertainment for human players and may often affect the course of game play, we remove it as a simplifying assumption for our initial Dixit AI challenge. Explaining one’s choices, however, is common among human players (Piccolo and Guerra 2010, Vayanou et al. 2019) and serves to show that choices were not made completely at random.

**Creative Captioning Problems in Dixit**

Winning a full game of Dixit involves maximizing one’s score earned across both storyteller and non-storyteller rounds. Here, we formalize specific problems and subproblems that a Dixit Agent (DA) would have to solve in order to win a game against human players. Of course, there are many other possible ways to frame the problems that Dixit poses; what we present here is one possible starting point.

**Storyteller round**

In the storyteller round, the DA begins with a hand \( H \) of six cards, each represented as a single color image: \( H = \{C_1, \ldots, C_6\} \).

Then, the DA must select one card \( C_{\text{target}} \) and produce a corresponding text-based phrase \( X_{\text{target}} \) that goes with that card. The phrase can be anything from the space of all possible utterances \( U_k \) of length \( k \) in the language in which the game is being played, i.e., \( X_{\text{target}} \in U_k \).

That is actually all that is required from the DA during the storytelling round. The rest of the round depends entirely on how the other players react.

So how does the DA produce a “winning” choice of \( C_{\text{target}} \) and \( X_{\text{target}} \)? This is actually a somewhat bizarre and ambiguous optimization problem.

Let \( n \in \{4, 5, 6\} \) be the total number of players in the game. Then, if the DA is the storyteller, there are \( n - 1 \) voting players in that round.

The score that the DA will receive as the storyteller depends on the number of players \( n_V \) that vote for its card:

\[
\text{score} = \begin{cases} 
0 & n_V = 0 \\
3 & 0 < n_V < n - 1 \\
0 & n_V = n - 1 
\end{cases} 
\]

For any choice of card \( C_i \) and phrase \( X_i \), the DA must essentially estimate the probability that the number of voting players \( n_V \) will lie in the desired range. If \( X_{\text{target}} \) is too specific to \( C_{\text{target}} \), then it is likely that \( n_V = n - 1 \). If \( X_{\text{target}} \) is not specific enough to \( C_{\text{target}} \), then it is likely that \( n_V = 0 \).

Given the ability to estimate this probability \( P_{\text{scoring}} \), the DA is then trying to choose some combination of \( C_{\text{target}} \) from its hand \( H \), and \( X_{\text{target}} \) from the set of all possible utterances \( U_k \) of length \( k \), that maximizes \( P_{\text{scoring}} \). We call this Storyteller Strategy #1:

\[
P_{\text{scoring}}(C_i, X_i) = P(0 < n_V < n - 1 \mid C_i, X_i) \quad (1) 
\]

\[
\left[ C_{\text{target}}, X_{\text{target}} \right] = \arg\max_{C_i \in H} \left\{ \arg\max_{X_i \in U_k} (P_{\text{scoring}}) \right\} \quad (2) 
\]

However, other players can also earn points during this round, based on whether they vote for the storyteller’s card (3 points), and also whether other players vote for their card (1 point per other player that has been deceived). So, while acting according to Eq. 2 can maximize the chances that the DA will earn 3 points, the DA’s net lead over the other players will vary, depending on how many other players vote for the storyteller’s card.

The net points earned by other players will be minimized if only one player votes for the DA’s card. Thus, a different strategy for the DA during storytellers round is to minimize the expected number of players \( E_{\text{votes}} = E[n_V] \) who might vote for the DA’s card, while keeping it above 0. We call this Storyteller Strategy #2.

\[
E_{\text{votes}}(C_i, X_i) = E[n_V \mid C_i, X_i] \quad (3) 
\]

\[
\left[ C_{\text{target}}, X_{\text{target}} \right] = \arg\min_{C_i \in H} \left\{ \arg\min_{X_i \in U_k} (E_{\text{votes}} \mid E_{\text{votes}} > 0) \right\} \quad (4) 
\]

**How Many Votes subproblem.** Either of the above strategies can be roughly decomposed into two subproblems. First, given any candidate pairing of a card and a phrase
$[C_i, X_i]$, the DA needs to be able to estimate how many other players are likely to vote for it, as in Eq. 1 or Eq. 3. As mentioned above, we require that the deck of cards is not previously known to the DA before gameplay, and so these probabilities cannot be “precomputed” for given cards and pre-selected target phrases.

Solving this subproblem requires different technical AI capabilities, including:

1. **Vision**: What does the card $C_i$ actually depict? What are the objects, characters, scene information, and affective and/or cultural implications?

2. **NLP**: What does the phrase $X_i$ actually mean? What is the proper parsing, word or phrase meanings, and affective and/or cultural implications?

3. **Story reasoning**: Given the card and phrase pairing, how can they be interpreted together to form a coherent visual+linguistic story?

4. **Social reasoning**: Given the card and phrase pairing, how many other players are likely to vote for this card, also relative to the other potential decoy cards that other players might produce in response to the phrase $X_i$?

**Find a Phrase subproblem.** Eq. 2 and Eq. 4 require the DA to choose a target card $C_{\text{target}} \in H$ and a target phrase $X_{\text{target}} \in \mathcal{I}_k$ from all possible utterances of length $k$.

One way to solve this subproblem could be to iterate through all $C_i$ in the DA's hand $H$, which only has six cards, and for each $C_i$, have some search strategy that generates a series of candidate phrases $X_i$ and evaluates each one according to the How Many Votes subproblem.

Then, the core remaining subproblem becomes how to generate a series of candidate phrases $X_i$ for a given $C_i$. Solving this subproblem requires:

1. **Vision**: As above.

2. **NLP and story reasoning**: What are possible “creative story captions” that could be applied to describe $C_i$?

**Non-storyteller round**

When the DA is not the storyteller, the round begins when the storyteller (another player) produces a target phrase $X_{\text{target}}$ for that round. In these rounds, the DA has two somewhat separable goals.

First, the DA must choose a card $C_{\text{decoy}} \in H$ from its hand that best lures other players into voting for it. During the voting phase, the DA will receive 1 point for each player that votes for its card. Thus, the DA should choose a card from its hand that maximizes the number of players likely to vote for it. As above, we let $n_V$ denote the number of other players voting for the DA’s card:

$$C_{\text{decoy}} = \arg\max_{C_i \in H} \{E_{\text{votes}} \mid C_i, X_{\text{target}}\} \tag{5}$$

Second, the DA will see a set $S$ of cards $C_i$ on the table (one from the storyteller, one from itself $C_{\text{decoy}}$, and one from each other player), and it must vote for the card $C_{\text{vote}}$ that it thinks is the storyteller’s card:

$$P_{\text{target}}(C_i) = P(C_i = C_{\text{target}} \mid X_{\text{target}}) \tag{6}$$

$$C_{\text{vote}} = \arg\max_{C_i \in S} \{P_{\text{target}}(C_i)\} \tag{7}$$

**How Many Votes subproblem variants.** In the non-storyteller round, when the DA is selecting its decoy card, it is solving something very similar to the How Many Votes subproblem as described above, except now it is in the DA’s interest to get as many players as possible to vote for its card. And, because the DA is searching its hand $H$, there are only six possible cards $C_i$ to choose from. Thus, a simple approach would be for the DA to iterate through all six cards in its hand, compute the expected number of votes for each, and select the card giving the maximum estimate.

Of course, as noted above, solving the How Many Votes subproblem is quite difficult and requires vision, NLP, story reasoning, and social reasoning.

Finally, when the Dixit agent has to vote on the card that it believes is the original storyteller’s card, it is again solving a variant of the How Many Votes subproblem. It can perform exhaustive search through the $n - 1$ available card options (one card from each player except its own), and for each one, estimate the probability of its being the storyteller’s card.

**End-Game Considerations**

The above equations describe several strategies that the DA can use to essentially maximize its own score. However, there are also situations in Dixit when the DA might need to instead shift strategies to prevent other players from scoring, for instance towards the end of a game if another player is very close to winning.

For example, suppose the DA is not the storyteller, and the player who is the storyteller is within 3 points of winning. Then, instead of using Eq. 7 to choose its vote, which maximizes the probability in Eq. 6, the DA might instead want to minimize this Eq. 6 probability, in order to prevent the storyteller from winning.

Many games have strategies that shift as gameplay progresses. In Dixit, all players can see the scoreboard at all times, and so while reasoning about the scores of other players might not always be strictly necessary to win, it does play a potentially useful (and potentially game-changing) role.

**Towards Creative Captioning: The Current State of the Art**

Creative captioning in general, and in particular the specific challenge we propose of winning a game of Dixit, touches on core problems for many subfields of AI, including (1) vision, (2) natural language processing, (3) story or narrative reasoning, and (4) social reasoning, among others. In this section, we discuss the current state of the art in each of these subfields individually and taken as an integrated whole.

**Vision**

Creative captioning requires several robust vision capabilities, as described (non-exhaustively) below.

**Object recognition: What is in the image?** The last eight years have seen a revolution in approaches to object recognition, due in part to advances in dataset size (Deng et al. 2009) and deep learning methods (Krizhevsky, Sutskever, and Hinton 2012). However, generalized object recognition is still a
difficult problem, for example when models are faced with new images that are more complex than training images (Recht et al. 2019) or that depict objects in unusual poses (Barbu et al. 2019) or sociocultural contexts (de Vries et al. 2019). Additional challenges emerge when considering not just photographic images but also artwork and other other visual styles of depiction (Hall et al. 2015) [Westlake, Cai, and Hall 2016]. Dixit game images in particular, as shown in Figure 1, are especially challenging for artificial vision systems because they include surreal elements (Florea, Florea, and Badea 2016).

Scene analysis: How are the objects related? In addition to identifying objects and entities in an image, creative captioning additionally requires understanding the scene, i.e., relationships among objects. Going beyond just identifying objects and their relationships (Dai, Zhang, and Lin 2017), however, creative captioning also requires inferring aspects of the relevance of the scene to common scenes, common sense interpretations such as inferring physical interactions among objects (Battaglia, Hamrick, and Tenenbaum 2013), cultural contexts, etc.

Affective analysis: What is the emotional content of an image? Creative captioning also requires inferring affective aspects of an image, including overall mood or tone (Machajdik and Hanbury 2010), facial expressions of characters (Zhao and Zhang 2016), etc.

Natural Language Processing/Understanding
In recent years, language models such as Bert (Devlin et al. 2018), GPT (Radford et al. 2018), and their derivatives (Liu et al. 2019) [Radford et al. 2019] [Brown et al. 2020] etc. have made substantial progress on many natural language tasks, ranging from question answering to story completion. Of these, story completion (e.g., HellaSwag (Zellers et al. 2019) and StoryCloze (Mostafazadeh et al. 2016)) is the most similar to creative captioning.

Story completion tasks, sometimes referred to as cloze tasks, combine language understanding with language generation. The datasets contain short (3-5 sentence length) stories, the first few sentences of which are provided as input to the system being tested. The system must then generate the rest of the story. This requires understanding the contents of the story, along with any implied commonsense reasoning and storyteller intentions. Humans perform incredibly well on these tasks—100% accuracy on StoryCloze (Mostafazadeh et al. 2016) and 95.6% accuracy on HellaSwag (Zellers et al. 2019). Yet, even the newest (at the time of writing) GPT model, GPT-3, performs significantly worse (Brown et al. 2020). This is likely because language models do not perform natural language understanding or commonsense reasoning, and instead find patterns and make connections across millions of training examples (Marcus and Davis 2020). We believe that this will cause language models to struggle on the creative captioning task as well, especially since generation must occur between modalities (i.e., generate language based on an image, or select an image based on language). On the other hand, language models have been successful on some creative tasks (e.g., poetry (Liao et al. 2019)), which suggests that creative captioning may not be entirely out of reach.

Other approaches combine knowledge and inference for language understanding. For example, (Lin, Sun, and Han 2017) encoded three types of commonsense knowledge as inference rules: event narrative knowledge, entity semantic knowledge, and sentiment coherence knowledge. They then learned an attention model which selected appropriate rules for a given question. This inference-based model outperformed several others, including a Deep Structured Semantic Model (Mostafazadeh et al. 2016) and an LSTM-based Recurrent Neural Network (Pichotta and Mooney 2016), on a version of the StoryCloze task. Others (Botschen, Sorokin, and Gurevych 2018) have found that incorporating knowledge from sources like FrameNet (Baker, Fillmore, and Lowe 1998) and Wikidata (Vrandečić and Krötzsch 2014) similarly improve performance on another cloze task (Habernal et al. 2017). While, to the best of our knowledge, such knowledge based approaches have not been tested on creative tasks, their strong performance on cloze tasks suggests that they may be able to handle the language interpretation component of creative captioning, as well.

Story Reasoning/Narrative Understanding
The “creative” part of creative captioning goes beyond traditional image captioning tasks, and their emphasis on veridical image description, to include more sophisticated interpretations of images and phrases. A creative captioning agent must be able to generate multiple alternatives when interpreting images, phrases, or both; and also to consider such interpretations at multiple levels of abstraction.

This class of capabilities is strongly tied to AI research in story reasoning / narrative understanding, as human interpretations of images and phrases often revolve around story-like conceptual constructs, like the “Monty Hall” example in Figure 1.

AI research on narrative reasoning observes that such reasoning often relies on an agent’s prior knowledge base of stories or story prototypes, as well as rich analogical reasoning to build or reason about new stories (Finlayson 2009). There are many open research questions in modeling story structures (Riedl and Young 2006), as well as how to elicit data for training story reasoning systems (Li et al. 2013).

Moreover, creative captioning exemplifies narrative reasoning that bridges both linguistic and visual inputs, requiring at some level unified conceptual representations that can span both modalities. While much AI research in narrative reasoning has relied on linguistic representations, there is also work on such reasoning in images (Cohn 2020) [Iyyer et al. 2017].

Social Reasoning
Creative captioning must be creative, but not so much so that it is uninterpretable; people must be able to understand the reference. This requires sufficient social reasoning to consider what connections others are likely to make, what cultural references they are likely to be aware of, and how they are likely to approach creative captioning more broadly. In the context of the Dixit game, the Dixit Agent (DA) must
also reason about the strategies other players are likely to pursue.

The most similar social reasoning problems to those posed by creative captioning and the Dixit game are in other game domains. For example, Hanabi and Werewolf have both been proposed as AI challenges (Bard et al. 2020; Toriumi et al. 2016) specifically because they require social reasoning for successful gameplay. In this section, we focus our discussion on these two games.

Hanabi is a cooperative card game, in which players work to construct ordered decks of cards (1-5) according to their colors (white, yellow, blue, green, red). Players are limited in both information and in communication: players cannot see their own cards, they have a limited number of hints to give each other, and those hints can only contain information about card color or number—not both. To succeed, players must consider not only the information explicitly given in a hint, but also the information implied by it. For example, if the red 1 has just been played, and a player is then given the hint that they have a red card, they might infer that the card is, in fact, a playable red 2.

Bard et al. (2020) present several baseline agents for the Hanabi challenge. These include both rule-based and learning agents. In a self-play setting, the rule-based agents outperform the learning agents. However, only the learning agents are tested in ad-hoc teams (i.e., teams of different agent types) because of the rigidity built into the rule-based agents. None of the agents were tested while playing on mixed teams with humans, and none explicitly took social reasoning into account. Yet, Eger et al. (2020) found that giving agents the ability to reason about the intents of their human teammates led to improved scores on mixed human-AI teams. Similarly, Liang et al. (2019) found that human Hanabi players are more likely to believe they are playing with other people when AI agents perform explicit social reasoning (in this case by considering the possible interpretations of implied information communicated by hints). This is even more likely to be true of Dixit, where metaphorical interpretation of communication is important to game play.

Unlike Hanabi, Werewolf is a competitive game in which winning strategies require some level of deception. At the beginning of gameplay, players are privately assigned roles, corresponding to one of two teams: townspeople and werewolves. While each werewolf knows who the other werewolves are, the townspeople do not know any other player’s role.

Each round is separated into a day phase and a night phase. During the day, there is open discussion. Townspeople strategize and attempt to discern who the werewolves are. Werewolves, on the other hand, try to throw the townspeople off their trail. At the end of the day phase, players vote for who they believe to be a werewolf and that person is removed from the game. At night, the werewolves select a townsperson, a victim, to also remove from the game. If there are more werewolves than townspeople at any point, the werewolves win. If however, all werewolves are voted out, the townspeople win.

The biggest challenge of the Werewolf game is the open conversation during the day, which requires complete conversational AI. To limit this complexity, Toriumi et al. (2016) limit both the number and type of utterances allowed for players in their challenge. Nonetheless, most approaches to Werewolf-playing agents base behavior on the game logs of human players, including transcription of the conversations between them (Hirata et al. 2016; Hancock et al. 2017; Kondoh, Matsumoto, and Mori 2018; Shoji et al. 2019) etc.). These conversations encode the speakers’ social reasoning, often explicitly by lying or calling out presumed lies. We believe that a similar approach (i.e., learning from observation of human players) may be fitting for a DA, as well.

Putting it All Together: Integrated Reasoning

A successful DA needs to have strong abilities in each of the subareas described above. Perhaps more importantly, however, it needs to integrate these abilities into a unified system. This requires being able to not only reason about multiple modalities (i.e., images and natural language) but also unify multiple reasoning styles (i.e., story understanding and social reasoning).

The systems that are closest to such integration are cognitive architectures (Anderson 2005; Langley and Choi 2006; Laird 2012; Forbus and Hinrichs 2017 etc.). Because they are designed as a single system that performs multiple types of reasoning over multiple modalities, they are well-positioned for a task like creative captioning. However, the state of the art in most most of the subproblems needed for creative captioning (i.e., visual perception, natural language processing, etc.) has been set by deep learning systems, rather than cognitive architectures. The team behind Watson found that a combination of statistical and knowledge-based approaches was necessary to beat humans at Jeopardy! (Ferrucci et al. 2010). Perhaps integrating approaches from deep learning and cognitive architecture will similarly lead to beating humans at Dixit, as well success in creative captioning more broadly.

Conclusion

We have identified creative captioning as a novel challenge for AI systems. To be successful at creative captioning, we argue that an agent must, at the very least, integrate visual perception, natural language understanding, and social reasoning. To that end, we have proposed the game Dixit as a domain for creative captioning, and identified intermediate subproblems that must be solved along the path to both successful play in Dixit and creative captioning overall. In the future, we will work toward solving these subproblems. We hope our colleagues will join us.

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